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NON-CONVENTIONAL MACHINING OF Al/SiC METAL MATRIX COMPOSITE

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NON-CONVENTIONAL MACHINING OF Al/SiC METAL MATRIX COMPOSITE

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Dedicated to my parents, Guide &Friends

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CERTIFICATE

This is to certify that the thesis entitled "NON-CONVENTIONAL MACHINING OF Al/SiC METAL MATRIX COMPOSITE" which is being submitted by DEBAPRASANNA PUHAN as partial fullfilment of Master of Technology degree in Production Engineering (Mechanical Engineering) during the academic year 2010-2012 in the Department of Mechanical Engineering, National Institute of Technology, Rourkela.

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DECLARATION

We hereby declare that the thesis entitled "NON-CONVENTIONAL MACHINING OF Al/SiC METAL MATRIX COMPOSITE" is a bonafied record of work done by me, as a functional part towards the fulfillment of Master of Technology degree in Production Engineering specialization (Mechanical) from National Institute of Technology, Rourkela during the academic year 2010-2012.

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ABSTRACT

In recent years, aluminum alloy based metal matrix composites (MMC) are gaining importance in several aerospace and automobile applications. Aluminum has been used as matrix material owing to its excellent mechanical properties coupled with good formability. Addition of SiC_p as reinforcement in aluminium system improves mechanical properties of the composite. In the present investigation, Al-SiC_p composite was prepared by powder metallurgy route. Powder metallurgy homogeneously distributes the reinforcement in the matrix with no interfacial chemical reaction and high localized residual porosity. SiC particles containing different weight fractions (10 and 15 wt. %) and mesh size (300 and 400) is used as reinforcement .Though AlSiC possess superior mechanical properties, the high abrasiveness of the SiC particles hinders its machining process and thus by limiting its effective use in wide areas. Rapid tool wear with poor performance even with advanced expensive tools categories it as a difficult-to-cut material. Non-conventional processes such as electrical discharge machining (EDM) could be one of the best suited method to machine such composites. Four machining parameters such as discharge current (I_p), pulse duration (Ton), duty cycle (τ),flushing pressure (Fp) and two material properties weight fraction of SiC_p and mesh size, and four responses like material removal rate (MRR), tool wear rate (TWR), circularity and surface roughness (Ra) are considered in this study. Taguchi method is adopted to design the experimental plan for finding out the optimal setting. However, Taguchi method is well suited for single response optimization problem. In order to simultaneously optimize multiple responses, a hybrid approach combining principal component analysis (PCA) and fuzzy inference system is coupled with Taguchi method for the optimization of multiple responses. The influence of each parameter on the responses is established using analysis of variances (ANOVA) at 5% level of significance. It is found that discharge current, pulse duration, duty cycle and wt% of SiC contribute significantly, where flushing pressure and mesh size of SiC_p contribute least to the multiple performance characteristic index.

Keywords: Powder metallurgy; Sintering; Heat Treatment; Electrical Discharge Machining; Taguchi Method; Principal Component Analysis; Fuzzy Inference System: Analysis of Variance; Weighted Principal Component Analysis; Thermo-Physical Modeling;

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Glossary of terms

Al/SiC	Aluminium Silicon Carbide
MMC	Metal Matrix Composites
PMC	Polymer Matrix Composites
CMC	Ceramic Matrix Composites
PM or P/M	Powder Metallurgy
XRD	X-Ray Diffraction
HT	Heat Treatment
EDM	Electrical Discharge Machining
MRR	Material Removal Rate
TWR	Tool Wear Rate
S/N	Signal to Noise
PCA	Principal Component Analysis
FIS	Fuzzy Inference System
WPCA	Weighted Principal Component Analysis
ANOVA	Analysis of Variance
MPC	Multi Performance Characteristics
MPCI	Multi Performance Characteristics Index

CHAPTER-1

BACKGROUND AND MOTIVATION

CHAPTER-1

BACKGROUND AND MOTIVATION

1.1 Introduction

Composite materials play an important role in the field of engineering as well as advance manufacturing in response to unprecedented demands from technology due to rapidly advancing activities in aircrafts, aerospace and automotive industries. These materials have low specific gravity that makes their properties particularly superior in strength and modulus to many traditional engineering materials such as metals. As a result of intensive studies into the fundamental nature of materials and better understanding of their structure property relationship, it has become possible to develop new composite materials with improved physical and mechanical properties. These new materials include high performance composites such as reinforced composites. Continuous advancements have led to the use of composite materials in more and more diversified applications. The importance of composites as engineering materials is reflected by the fact that out of over 1600 engineering materials available in the market today more than 200 are composite [1].

1.2 Composites

The typical composite materials are engineered or naturally occurring materials made from two or more constituent materials with significantly different physical or chemical properties which remain separate and distinct at the macroscopic or microscopic scale within the finished structure. The constituents retain their identities, that is, they do not dissolve or merge completely into one another although they act in concert.

The individual materials that make up composites are called constituents. Most composites have two constituent materials: a binder or matrix (polymers, metals, or ceramics) and reinforcement (fibers, particles, flakes, and/or fillers). The reinforcement is usually much stronger and stiffer than the matrix, and gives the composite its good properties. The matrix holds the reinforcements in an orderly pattern. Because the reinforcements are usually discontinuous, the matrix also helps to transfer load among the reinforcements. Some authors defined composite as:

Berghezan [2] stated as “The composites are compound materials which differ from alloys by the fact that the individual components retain their characteristics but are so incorporated into the composite as to take advantage only of their attributes and not of their shortcomings”.

There are two major reasons for the current interest in composite materials. The first is simply the need for materials that will outperform the traditional monolithic materials. The second and more important in the long run is that composite offer engineers the opportunity to design totally new materials with the precise combination of properties needed for specific tasks.

1.2.1 Classification of composites

Composites are classified in various ways by different authors but in simplest and broadest sense this may be classified as (i) Natural, and (ii) Man-made or synthetic (Figure 1.1).

The composites that occur in nature are called natural composites such as, wood (composed of cellulose fires and lignin support), human or animal body (composed of bones and tissues). Bones, sea shells and elephant tusk are also considered as the examples of natural composites provided by nature [3].

The reinforced composites are classified in two ways: (i) on the basis of matrix used and (ii) on the basis of the geometry of the reinforcement. Based on the matrix phase used, multiphase composites are divided into three categories:

a) Polymer-matrix composites (PMCs).
b) Ceramic-matrix composites (CMCs).
c) Metal-matrix composites (MMCs).

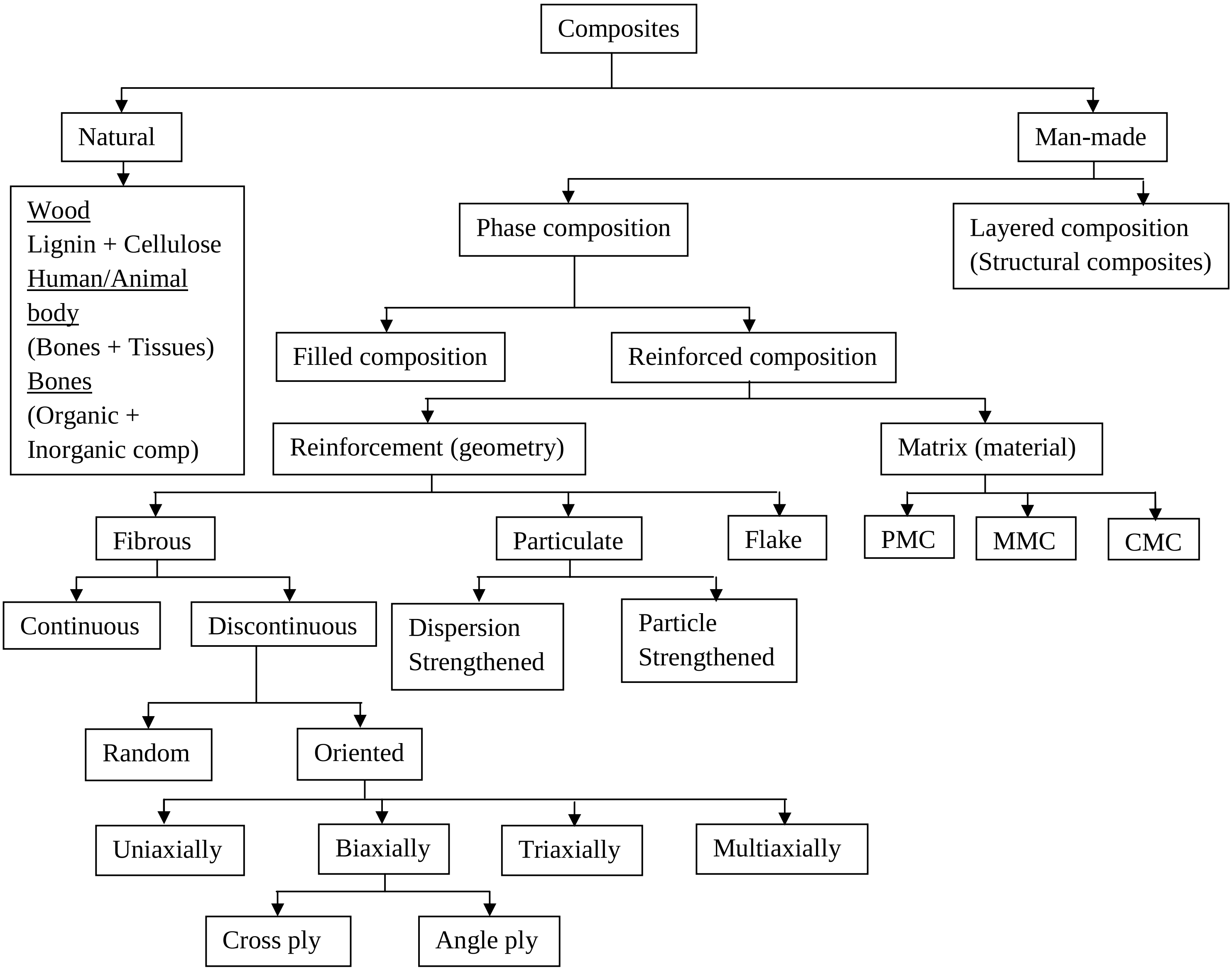


Figure 1.1 Classification of composites

1.2.2 Components of a composite material

A composite material is a material consisting of two or more physically and chemically distinct parts, suitably arranged, having different properties respect to those of the each constituent parts. In practice, most composites consist of a bulk material (the 'matrix'), and a reinforcement of some kind, added primarily to increase the strength and stiffness of the matrix.

The material, which uses as matrix must bind and hold firmly the reinforcing phase in position within. The matrix isolates the materials from one another in order to prevent abrasion and formation of new surface flaws and acts as a bridge to hold the materials in place. A good matrix should possess ability to deform easily under applied load, transfer the load onto the materials and evenly distributive stress concentration. A few inorganic materials, polymers and metals have found applications as matrix materials in the designing of structural composites, with commendable success. These materials remain elastic till failure occurs and show decreased failure strain, when loaded in tension and compression. Some generally used as matrices are Polymer matrices [4, 5], Ceramic matrices [6] and Metal matrices [7].

Reinforcing constituents in composites indicates to provide the strength that makes the composite what it is. But they also serve certain additional purposes of heat resistance or conduction, resistance to corrosion and provide rigidity. Reinforcement can be made to perform all or one of these functions as per the requirements. A reinforcement that embellishes the matrix strength must be stronger and stiffer than the matrix and capable of changing failure mechanism to the advantage of the composite. This means that the ductility should be minimal or even nil the composite must behave as brittle as possible.

1.3 Metal matrix composite

In a material composite, when the matrix is a metal or an alloy, we have a "Metal Matrix Composite (MMC = Metal Matrix Composite). The matrix is essentially a metal, but seldom a pure one. Except sparing cases, it is generally an alloy. Matrix material distinguishes the MMC from the unreinforced matrix interms of increased strength, higher elastic modulus, higher service temperature, improved wear resistance, high electrical and thermal conductivity, low coefficient of thermal expansion and high vacuum environmental resistance. These properties can be attained with the proper choice of matrix and reinforcement. The main function of the matrix is to transfer and distribute the load to the reinforcement. This transfer of load depends on the bonding which depends on the type of matrix and reinforcement and the fabrication technique [8].

Generally MMCs are classified according to type of used reinforcement and the geometric characteristics of the same. Normally, the main classification of composites can be made in the form of reinforcement groups into two basic categories:

a. Continuous reinforcement composites, constituted by continuous fibers or filaments;
b. Discontinuous reinforced composites, containing short fibers, whiskers or particles.

1.3.1 Characteristics of MMCs

Metal Matrix Composites, alternatives to conventional materials, provide the specific mechanical properties necessary for elevated as well as ambient temperature applications. The performance advantages of these materials include their tailored mechanical, physical and thermal properties in light of their low density, high specific modulus, high strength, high thermal conductivity, good fatigue response, control of thermal expansion, high abrasion and wear resistance, etc. Some of the typical applications of MMCs include their use in fabrication of satellite, missile, helicopter structures, structural support, piston, sleeves and rims, high temperature structures, drive shaft, brake rotors, connecting rods, engine block liners various types of aerospace and automotive applications etc. The superior mechanical properties of MMCs drive their use. An important characteristic of MMCs, however, and one they share with other composites. This can be possible by appropriate selection of matrix materials, reinforcements, and reinforcement orientations and also possible to tailor the properties of a component to meet the needs of a specific design. The performance of these materials renders their characteristics in terms of physical and mechanical peculiarity, depend on the nature of the two components (chemical composition, crystalline structure, and in the case of reinforcement, shape and size), the volume/weight fraction of the adopted reinforcement and production technology. In general we can say that metal matrix composites utilize at the same time the properties of the matrix (light weight, good thermal conductivity, ductility) and of the reinforcement, usually ceramic (high stiffness, high wear resistance, low coefficient of thermal expansion). Material characterization can be obtained by comparing the basic metal component in terms of high values of specific strength, stiffness, wear resistance, fatigue resistance and creep, corrosion resistance in certain aggressive environments. However, cause to the presence of the ceramic component, ductility, toughness and fracture to the coefficients of thermal expansion and reduction of thermal conductivity.

The different variety of MMCs has different distinguishable properties. Factors influencing their characteristics include:

a. Reinforcement properties, form, and geometric arrangement.
b. Reinforcement volume/weight fraction.
c. Matrix properties, including effects of porosity.
d. Reinforcement-interface properties.
e. Residual stresses arising from the thermal and mechanical history of the composite.
f. Degradation of the reinforcement resulting from chemical reactions at high temperatures, and mechanical damage from processing, impact, etc

1.3.2 Advantages and Disadvantages of MMC

Compared to monolithic metals, PMC and CMCs, MMCs have:

a. Higher strength-to-density ratio and stiffness-to-density ratios.
b. Better fatigue resistance and lower creep rate.
c. Better elevated temperature properties.
d. Lower coefficients of thermal expansion.
e. Better wear resistance and radiation resistance.
f. Higher temperature capability with fire resistance.
g. Higher transverse stiffness and strength.
h. No moisture absorption and no outgassing.
i. Higher electrical and thermal conductivities.
j. Fabricability of whisker and particulate-reinforced MMCs with conventional metalworking equipment.

Some of the disadvantages of MMCs compared to monolithic metals, PMCs and CMCs are

a. Higher cost of some material systems.
b. Relatively immature technology.
c. Complex fabrication methods for fiber-reinforced systems (except for casting).
d. Limited service experience.

1.4 Matrix material

The matrix material should be carefully chosen depending upon its properties and behaviour with the reinforcement. As it is the primary constituent in MMC, the matrix alloy should be chosen only after giving careful consideration to its chemical compatibility with the reinforcement, to its ability to wet the reinforcement, and to its own characteristics properties and processing behaviour [9, 10]. The best properties can be obtained in a composite system when the reinforcement whiskers or particulates and matrix are as physically and chemically compatible as possible. Special matrix alloy compositions, in conjunction with unique whisker coatings, have been devised to optimize the performance of certain metallic composites [11, 13].

Researchers have proposed a lot of materials as the matrix material depending on their properties. Taya and Arsenault [13] have suggested materials like Al, Ti, Mg, Ni, Cu, Pb, Fe, Ag, Zn, Sn and Si on the basis of oxidation and corrosion resistance properties. Among these Al, Ti, Mg are used widely. The most common metal alloys in use are based on Aluminium and Titanium. Both of them are low density materials and are commercially available in a wide range of alloy compositions. Other alloys are also used for specific cases, because of their own advantages and disadvantages. Beryllium is the lightest of all structural materials and has a tensile modulus greater than that of steel, but it is extremely brittle, rendering it unsuitable for general purpose use. Magnesium is light, but is highly reactive to Oxygen. Nickel and Cobalt based super alloys have also found some use, but some of the alloying elements present in the matrices have been found to have undesirable effect (promoting oxidation) on the reinforcing fibers at high temperatures. Aluminum is one of the best materials for matrix because of its unique combination of excellent mechanical and electrical properties of good corrosion resistance low density and high toughness with high conductivity [14]. Moreover, Al is cheaper than other light metals like magnesium (Mg). The other advantage of using Al as matrix of MMCs is its corrosion resistance which is very important for using composites in different environments [15]. Magnesium and its alloys do not compare favorably with aluminium alloys in terms of absolute strength though; they are lightest materials and good combination of low density and excellent machinability as compared with other structural materials [16]. Aluminum based metal matrix composites (MMCs) offer potential for advanced structural applications when high specific strength and modulus, as well as good elevated temperature resistance, high service temperature and specific mechanical properties are important.

1.5 Reinforcement

Reinforcement increases the strength, stiffness and the temperature resistance capacity and lowers the density of MMC. In order to achieve these properties the selection depends on the type of reinforcement, its method of production and chemical compatibility with the matrix and the following aspects must be considered while selecting the reinforcement material. Reinforcements are characterized by their chemical composition, shape, dimensions, and properties as in gradient material and their volume fraction and spatial distribution in the matrix [17]. Although the largest improvement in properties (strength and stiffness) is obtained with the introduction of fiber reinforcements but the properties of fiber-reinforced composites are not isotropic. Particulate-reinforced MMC show the advantage of nearly isotropic properties and cost-effectiveness. Furthermore, an additional advantage of the particulate-reinforced over fiber reinforced MMC is that most existing processing techniques can be used for fabrication and finishing of the composites, including hot rolling, hot forging, hot extrusion and machining [18-21].

It is proven that the ceramic particles are effective reinforcement materials for aluminium and its alloy to enhance the mechanical and other properties. Typically these ceramics are oxides, carbides and nitrides. These are used because of their combinations of high strength and stiffness at both room and elevated temperatures. Common reinforcement elements are SiC, $A1_2O_3$, TiB_2, thorium, boron and graphite. The use of graphite reinforcement in a metal matrix has a potential to create a material with a high thermal conductivity, excellent mechanical properties and attractive damping behaviour at elevated temperatures. However, lack of wettability between aluminium and the reinforcement, and oxidation of the graphite lead to manufacturing difficulties and cavitations of the material at high temperatures [22]. Alumina and other oxide particles like TiO_2 etc. have been used as the reinforcing particles as it is found that these particles increase the hardness, tensile strength and wear resistance of aluminium metal matrix composites [23]. Silicon carbide (SiC) ceramics are promising candidates in the field of high-temperature structural materials due to their excellent oxidation, corrosion, and creep resistance [24]. Silicon carbide particle (SiC_p) reinforced aluminium-based MMCs are among the most common MMC and commercially available ones due to their economical production [25].

1.6 Reinforcement characteristics

Researchers have documented that the mechanical and electrical properties of an Al-based MMC is highly influenced by the particle size, distribution and fraction (weight/volume). Large size particles has a tendency towards fracture whereas, small size particles increase the strength exhibit superior strength and failure strain of MMC [26, 27]. A uniform reinforcement distribution is essential for effective utilization of the load carrying capacity of the reinforcement. Non-uniform distributions form streaks or clusters of reinforcement with their attendant porosity, all of which lowered ductility, strength and toughness of the material. The clustering of the particulate reinforcement during MMC production has an important influence on MMC properties. Avoid this gives better micromechanical properties [28]. Wt% of SiC has direct influence on the mechanical properties of AlSiC [29]. SiC particulates affect the micro structural properties of MMC by increasing its density, sintering temperature and hardness. Best characteristics obtained at 10 to 15 wt% SiC presences [27]. The electrical conductivity of composites decreased with increase in the volume fraction and decrease in size of the reinforcement particles [30].

1.7 Al/SiC MMC

Aluminum is used widely as a structural material especially in the aerospace industry because of its light weight properties. Its low strength and low melting point of aluminum were always a problem. An effective method of solving these problems is to use a reinforced element such as SiC particles and whiskers. The high-strength, high-specific modulus and low density aluminium alloy-based composites with silicon carbide reinforcement have generated significant interest in the industries where strength to weight ratio is the primary concern. The combination of light weight, environmental resistance and useful mechanical properties such as modulus, strength, toughness and impact resistance has made aluminium alloys well suited for use as matrix materials. Moreover, the melting point of aluminium is high enough to satisfy many application requirements. Among various reinforcements, silicon carbide is widely used because of its high modulus and strengths, excellent thermal resistance, good corrosion resistance, good compatibility with the aluminium matrix, low cost and ready availability. The main objective of using silicon carbide reinforced aluminum alloy composite system for advanced structural components to replace the existing super alloys [31, 32].

Aluminum and its alloys have the most attention, as matrix materials for MMCs and the most common reinforcement is SiC. Aluminum (commercially pure having an assay of >99% of Aluminum) and SiC particulates have been used for the MMC fabrication in the present investigation.

1.8 Production Technologies for MMCs

In recent years the prospective of metal-matrix composite (MMC) materials for considerable improvement in performance over conventional alloys has been documented widely. However, their production costs are still relatively high. There are several production techniques available to manufacture the MMC materials: there is no unique route in this respect. Production process needs the fundamental about the MMCs, to determine their mechanical and physical properties. Since the technology that concerns the various manufacturing processes, especially as regard their history, are often customized by individual manufacturers to suit the specific necessity.

The production techniques can vary considerably depending on the choice of material and reinforcement and of the types of reinforcement. In general the most common manufacturing MMC technologies are divided primarily into two main parts: the primary and the secondary. The primary processing is the composite fabrication by combining ingredient materials (powdered metal and loose ceramic particles, or molten metal and fibre performs), but not necessarily to final shape or final microstructure. The secondary processing instead is the step which obviously follows primary processing, and its aim is to alter the shape or microstructure of the material (shape casting, extrusion, forging, heat-treatment, machining). Secondary processing may change the constituents (phase, shape) of the composite. The processing methods used to manufacture MMCs can be grouped as follows.

1.8.1 MMCs fabrication methods (primary processing)

Fabrication of MMCs is the primary processing route of its production. A basic classification, about the technological methods for MMCs, takes account of the state where the constituents during the primary cycle of production. Preparation of MMCs can be broadly divided into three categories of fabrication techniques. And these are further sub-categories in different techniques. They are:

1. *Liquid phase fabrication*

Liquid state processing of MMCs find wide adoption because of the advantages associated in terms as lower cost involvements for obtaining liquid metals than metal powder; possibility of producing various complex shapes using liquid metals with considerable ease by adopting methods already developed in the casting industry . Some techniques documented by researchers are infiltration [33, 34], dispersion [35], spraying [36], in-situ fabrication [37], squeeze casting [38], stir casting [39], and compocasting [40].

Conversely liquid state processing also suffers from a number of drawbacks that include lack of reproducibility linked with incomplete control of the processing parameters and some undesirable chemical reactions at the interface of the liquid metal and the reinforcement.

2. *Solid phase fabrication*

Solid states processing of MMCs are generally used to obtain the highest mechanical properties in the resulting MMCs. This process is adopted to obtain fine grained control over the composite microstructure and the reinforcement distribution. Particularly the discontinuous reinforcement MMCs are processed in this route to obtain enhanced mechanical properties. This is because segregation effects and brittle reaction product formation are a bare minimum as against the liquid state processing route. In present day some adopted methods of MMCs are diffusion bonding [41] and powder metallurgy [42, 43].

3. *Vapor state processing*

Vapor deposition is a primary process where the matrix is deposited from the vapor phase into individual reinforcement elements of the ingredient. It may be noted that there is little or no mechanical disturbance of the interfacial region and large adhesion in between matrix/reinforcement without any chemical reaction. The matrix is deposited by plasma spraying [44] or by physical vapor deposition [45] or by chemical vapor deposition [45, 46].

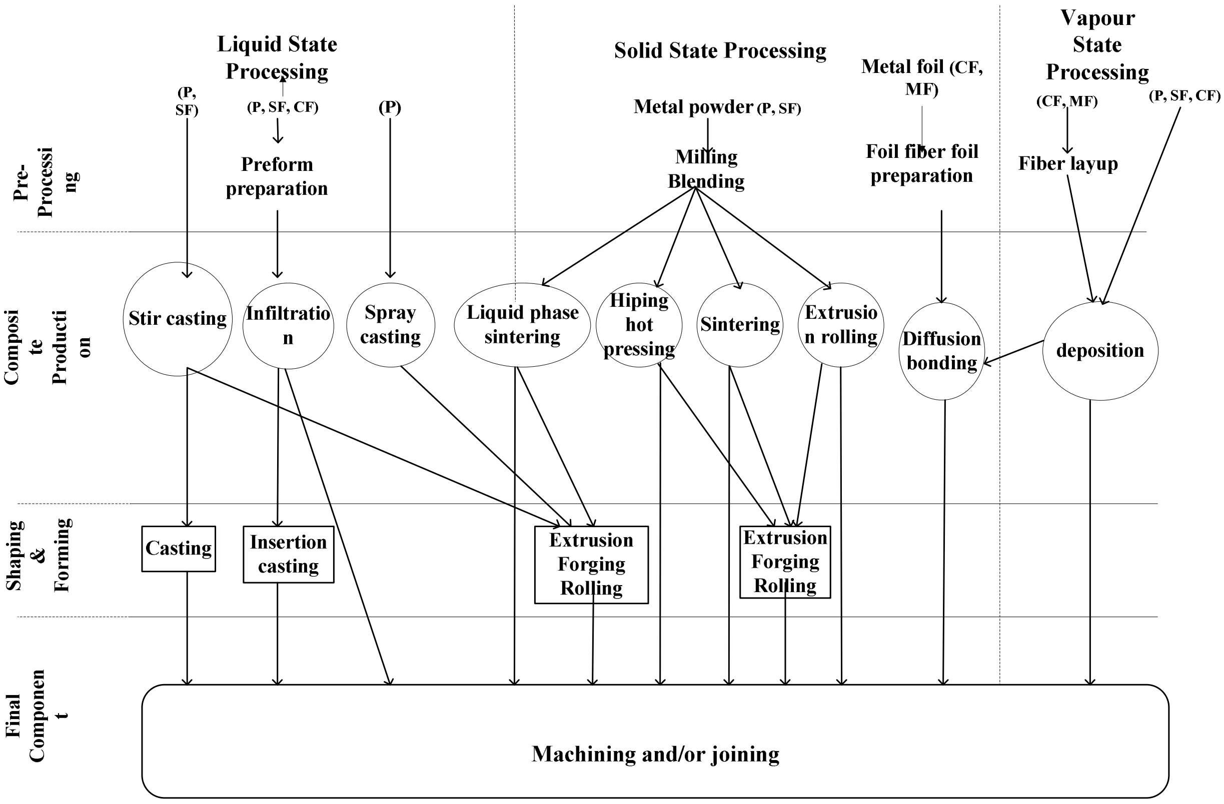
1.8.2 MMCs machining methods (secondary processing)

The secondary processing route is the machining where; composite materials offer the benefits of part integration and thus minimize the requirement for machining operations. However, machining operations cannot be completely avoided and most of the components have some degree of machining. Machining of metals is very common and is easily performed; however, the machining of metal matrix composites poses several challenges as difficult to attain dimensional accuracy, tool life is usually shorter because of the abrasive nature of the composite etc. Generally machining on MMCs is carried out by both the conventional and non-conventional method of machining.

Conventional method: Cutting tools similar to those in metal machining are used for composites as well. However, high-speed steel (HSS) tools are coated with tungsten carbide, titanium nitride, or diamond to avoid excessive wear on the tool. In terms of tool life, carbide tools are superior, especially if carbide grades of fine grain size are used. Polycrystalline Cubic Nitride (PCBN) and polycrystalline diamond (PCD) tools are extensively used for conventional machining. The main problem while doing machining with high speed steel like conventional tools and methods on MMCs is the extensive tool wear caused by the very hard and abrasive reinforcements [47-52]. Li and Seah [53] observed that tool wear is influenced by the percentage, size and density of the reinforcement. To cope up with such problems authors had suggested some advanced tooling techniques. Pramanik et al. [54] had suggested a rotary circular tooling system (RCT) with a circular insert, which exhibited good wear resistance and extended tool life. Using coated tools in place of uncoated tools gave less tool wear and good surface finish at higher speeds [55]. Carbide tools, either uncoated or coated, withstand significant levels of tool wear after a very short period of machining [56]. Cutting tools based on electroplated diamond-grinding wheel/ poly crystalline diamond (PCD) and with hybrid composites like polycrystalline cubic boron nitride (PCBN) have been used for some years for the machining of such abrasive composites as fiber-reinforced composites [50,57,58]. The high production cost along with high and unsuitable surface finish hinder the wide application of these advanced tools of machining Al/SiC [57-60]. Such problems are frequently occurred while machining MMCs and it is prominent in the case of AlSiC MMC as it employs SiC its reinforcement material. Thus AlSiC composite is categorized as difficult-to-cut material, though its hardness is so high.

Non-conventional method: Non-conventional machining methods are gaining applications in wider engineering areas due to their ability to produce complex shapes on difficult-to-cut especially hard materials. The difficult-to-cut materials are machined smoothly by the non-conventional machining processes as there is no direct contact between tool and workpiece. Non-conventional machining processes such are electrical discharge machining (EDM), electro-chemical machining (ECM), laser beam machining (LBM) and abrasive water jet (AWJ) machining offer effective alternatives [61-65]. Poor surface finish on the work piece in AWJ and high thermal damage on the workpiece in ECM and LBM as compared to EDM limits their application on machining Al/SiC MMC [61]. Material with high hardness and high strength such as super alloys, composites, advanced ceramics etc with close precision and surface finish can be done by EDM satisfactorily [66-68]. Thus, EDM becomes an optimal choice in machining of AlSiC composite owing to its easy operation and production of high quality products.

The schematic diagram of the complete production process is shown in Figure 1.2.



P = Particle Reinforced MMC, SF = Short Fiber Reinforced MMC, CF = Continuous Fiber Reinforced MMC, MF = Monofilament MMC

Figure 1.2 Schematic overview of the production processes about MMCs

1.9 Research objectives

Though technological barriers exist, as in most technology areas, it is important to overcome them by developing proper understanding of process with related attributes. Exhaustive literature review reveals that, though MMCs are getting more attention than other reinforced composites still, its processing is in infant stage. More researches need to be required for effective production of AlSiC metal matrix composite.

Based on the guiding principles, the objective of the present research are as follows:

- Processing of Al/SiC_p by powder metallurgy method to achieve desire properties.
- Electrical Discharge machining on MMC.
- Analysis of experimental results using statistical methods.
- Optimum parameters selection for overall improvement in machining process.

1.10 Thesis outline

The remainder of this thesis is organized as follows:

- Chapter 1: Introduction

This chapter attempts to give an insight to the work undertaken and highlights the procedure adopted in the investigation.

- Chapter 2: Literature review

Includes a literature review to provide a summary of the base of knowledge already available involving the issues of interest. Previous researches in this field done by other researchers, their findings have been revisited and correlated prior to start of the current work. The help of work carried out by these researchers has been referred to wherever necessary to explain and support the present experimental findings. Inferences drawn from these reviews have been used to suitably design and modify the experimental design. Hence, this chapter serves as a base for the next chapter.

- Chapter 3: Experimental details

This chapter is indented to explain the experimental procedure adopted in the present investigation along with the experimental arrangements and details of experimental procedures. The instrument/ apparatus and the prescribed experiments carried out. The instruments/ apparatus and the prescribed experimental norms as adopted in the present investigations have been explained in details.

- Chapter 4: Methodology adopted

  This chapter is used to state and explain two present day optimization methods. Using these methods multi-responses are easily optimized and optimal machining parameter setting is calculated.

- Chapter 5: Results and discussions

This chapter houses the results in the form of tables, graphs, SEM – micrographs etc. which have been generated while carrying out the investigations. This also contains a detailed discussion of the results made on the basis of the experimental data.

- Chapter 6: Conclusions

  Basing on experimental findings, some useful conclusions has been drawn and scope of future work are given in this part of thesis.

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CHAPTER 2

LITERATURE SURVEY

CHAPTER-2

LITERATURE SURVEY

2.1 Introduction

The purpose of literature review is to provide background information on the issues to be considered in this thesis and to emphasize the importance of the present study. The literature survey is carried out as a part of the thesis work to have an overview of the properties, preparation and machining of metal matrix composites. To understand these physical-chemical processes requires a comprehensive study of the composites production at different parameters of manufacturing. A lot of researches are being carried out to find out an effective way of production, characterization and optimization of Aluminium-Silicon carbide metal matrix composite with superior mechanical properties.

2.2 Powder metallurgy

Particle reinforced metal–matrix composites have been considerably investigated in recent researches. Generally, this type of composites is produced using stir casting methods, and there have been fewer investigations on producing them by powder metallurgy techniques.

Powder metallurgy has the advantage of producing net-shape components minimizing machining process which is a great problem in case of aluminum silicon carbide composite as a result of high tool wear due to abrasiveness of the hard SiC particles. Also the machining process causes cracking of SiC particles and debonded matrix-reinforcement underneath the machined surface [69].Using powder metallurgy (PM) method to produce aluminum composites reinforced with SiC particulates produce a homogenous distribution of reinforcement in the matrix. While other methods of production like casting and thixoforming have the problems of reinforcement segregation and clustering, interfacial chemical reactions, high localized residual porosity and poor interfacial bonding. The rest of the production method such as spray deposition is very expensive which render its application [70]. The main advantage of P/M over other methods, such as liquid and vapor state processing, is the relatively low processing temperature, which may avoid undesired interfacial reactions between matrix and reinforcement [71]. Several authors have reported that desired mechanical properties such are hardness, density, yield strength and thermal conductivity could be easily achieved and controlled by varying different processing routes like compaction pressure, sintering temperature of powder metallurgy method [43, 72]

In Powder metallurgy method by increasing sintering temperature above the melting point of matrix metal not only breaks oxidation layer and fills porosity but also increases micromechanical properties [69]. Ice quenching of AlSiC MMC followed by artificial ageing for 6 h resulted in better mechanical properties of matrix alloy and its composites [73]. In addition, P/M allows a great degree of freedom in tailoring the microstructure (e.g., volume fraction, size and morphology of the reinforcement) [74].

2.3 Electrical Discharge Machining (EDM)

EDM has been a mainstay of manufacturing for more than six decades, providing unique capabilities to machine “difficult-to-machine” materials with desire shape, size, and required dimensional accuracy. Its distinctive attribute of using thermal energy to machine electrically conductive materials, regardless of hardness, has been an advantage in the manufacturing of mould, die, surgical, automotive and aeronautic components. It is essential especially in the machining of super tough, hard and electrically conductive materials such as the new space age alloys. It is better than other machining processes in terms of precision, quality characteristics and the fact that hardness and stiffness of a workpiece material is not important for the material removal. Though EDM has become an established technology, and commonly used in manufacturing of mechanical works, yet its low efficiency and poor surface finish have been the vital matter of concern. Hence, the investigations and improvements of the process are still going on, since no such process exists, which could successfully replace the EDM.

2.3.1 Mechanism of Material Removal in EDM

Electrical discharge machining is the most widely-used non-conventional machining process. Despite the fact that the mechanism of material removal of EDM process is not yet completely understood and is still debatable, the most widely established principle is the conversion of electrical energy it into thermal energy through a series of discrete electrical discharges occurring between the electrode and workpiece immersed inside a dielectric medium and separated by a small gap. Material is removed from the workpiece by localized melting and even vaporization of material. The sparks are created in between two electrodes in presence of dielectric liquid. A simple explanation of the erosion process due to the discharge is presented in. There is no mechanical contact between the electrodes (held at a small distance) and a high potential difference is applied across them.

The material removal mechanisms are been reported differently by many authors. Singh and Ghosh [75] showed that the electrostatic forces and stress distribution acting on the cathode electrode were the major causes of metal removal for short pulses. Gadalla and Tsai [76] elucidated the material removal of WC-Co composite to the melting and evaporation of disintegrated Co followed by the dislodging of WC gains, which have a lower electrical conductivity on the other hand, Lee and Lau [77] argued that thermal spalling as well contributes to the mechanism of material removal during the sparking of composite ceramics due to the physical and mechanical properties promotes abrupt temperature gradients from normal melting and evaporation.

2.3.2 EDM process parameters

As per the discharge phenomena explained earlier, some of the important process parameters which influence the responses are:

Discharge current (Ip): It is the most important machining parameter in EDM because it relates to power consumption of power while machining. The current increases until it reaches a preset level which is expressed as discharge current.

Discharge voltage (V): It is the open circuit voltage which is applied between the electrodes. The discharge voltage de-ionizes the dielectric medium, which depends upon the electrode gap and the strength of the dielectric, prior to the flow of current. Once the current flow starts, the open circuit voltage drops and stabilizes the electrode gap. It is a vital factor that influences the spark energy,

Pulse-on time (T_{on}): It is the time during which actual machining takes place and it is measured in µs. In each discharge cycle, there is a pulse on time and pause time/Pulse off time, and the voltage between the electrode and workpiece is applied during Ton duration. The longer the pulse duration higher will be the spark energy that creates wider and deeper crated.

Pulse-off time or pause time (T_{off}): In a cycle, there is a pulse off time or pause time during which the supply voltage is cut off as a consequence the Ip diminisisses to zero. It is also the duration of time after which the next spark is generated and is expressed in µs analogous to Ton.

Since, the dielectric must de-ionized after sparking and regain its strength, it required some time and moreover the flushing of debris also takes place during the T_{off} time.

Duty cycle (τ): It is the ratio of pulse on-time and the pulse period. It is expressed in %. Duty cycle is defined in the equation 3.1.

$$\tau = \frac{T_{on}}{T_{on} + T_{off}} \times 100 \tag{2.1}$$

Flushing Pressure (f_p): Flushing is an important factor in EDM because debris must be removed for efficient cutting, moreover it brings fresh dielectric in the inter electrode gap. Flushing is difficult if the cavity is deeper, inefficient flushing may initiate arcing and may create unwanted cavities which can destroys the workpiece. There are several methods generally used to flush the EDM gap: jet or side flushing, pressure flushing, vacuum flushing and pulse flushing.

Polarity: Polarity refers to the potential of the workpiece with respect to tool i.e. in straight or positive polarity the workpiece is positive, whereas in reverse polarity workpiece is negative. Varying the polarity can have dramatic effect, normally electrode with positive polarity wear less, whereas with negative polarity cut faster.

2.3.3 EDM performance measures

A considerable number of research investigations have been paying attention of composites on approach of yielding optimal EDM performance measures of high material removal rate (MRR), low tool wear rate (TWR) , low surface roughness (R_a) and acceptable circularity (r_1/r_2) in the field of electrical discharge machining [78-82]. This section provides a study into each of the performance measures and the scheme for their enhancement. In past, significant improvement has been carried out to enhance productivity, accuracy, and the versatility of EDM process. The key issue is to pick the process parameters such as Ip, T_{on}, τ and flushing pressure, in such a way that MRR and circularity increases; and concurrently TWR and surface roughness should diminish. However, it is difficult to establish the relationship between EDM process parameters and responses because the process is too complex in nature. Therefore, design of experiment approach is adopted to develop a process model using experimental data and studying the influence of process parameters on responses leading to optimal parameter setting.

Khan et al. [83] discuss the performance about the shape configuration of the electrode. The maximum MRR was found for round electrodes followed by square, triangular and diamond shaped electrodes. However, the highest EWR were found for the diamond shaped electrodes. Subsequently, Khan [84] reported overall performance comparison of copper and brass electrodes and observed that the highest MRR was observed during machining of aluminium using brass electrodes. Comparatively low thermal conductivity of brass as an electrode material does not allow the absorption of much heat energy, and most of the heat is utilized in the removal of material from aluminium workpiece at a low melting point but more wear occurred than copper. Copper has high melting point and conductivity than brass.

Karthikeyan et al. [31] developed mathematical models for optimizing EDM characteristics such as the MRR, TWR and the surface roughness on aluminium silicon carbide particulate composites, using full factorial design. The process parameters taken in to consideration were Ip, Ton and the percent volume fraction of SiC present in LM25 aluminium matrix. Dhar et al. [85] estimated the effect of Ip, Ton, and V on MRR, TWR on EDM of Al-4Cu-6Si alloy-10 wt. % SiC_P composites. Using three factors, three level full factorial designs, a second order non-linear mathematical model has been developed for establishing the relationship among machining parameters. It was revealed that the MRR and TWR increase with increase in Ip and Ton. El-Taweel [86] investigated the correlation of process parameters in EDM of CK45 steel with Al-Cu-Si-TiC composite produced using powder metallurgy technique and evaluated MRR and TWR. It is found that such electrodes are more sensitive to Ip and Ton than conventional electrodes. To achieve maximum MRR and minimum TWR, the process parameters are optimized and on experimental verification the results are found to be in good agreement. Dvivedi et al. [87] identified the machining performance in terms of MRR and TWR by obtaining an optimal setting of process parameters (Ton, Toff, Ip, and fp) during EDM of Al 6063 SiCp metal matrix composite. It was revealed that Ip is predominant on MRR than other significant parameters. MRR increases with increasing Ip and Ton up to an optimal point and then dropped. Wang and Lin [88] investigated the feasibility and optimization of EDM for inspecting the machinability of W/Cu composites using the Taguchi method utilizing L_{18} orthogonal table to obtain the Ip, Ton, τ and V in order to explore the MRR and TWR. Chiang [89] had explained the influences of Ip, Ton, Tau and voltage on the responses; MRR and electrodes wear and surface roughness. The experiments were planned according to a CCD on

Al_2O_3+TiC workpiece and the influence of parameters and their interactions were investigated using ANOVA. A mathematical model was developed and claimed to fit and predict MRR accurately with a 95% confidence. The main two significant factors affecting the response were Ip and τ.

2.4 Multi-objective optimization

In composites, materials are combined in such a way as to enable us to make better use of their virtues while minimizing to some extent the effects of their deficiencies. This process of optimization can release a designer from the constraints associated with the selection and manufacture of MMCs. He can make use of tougher and lighter materials, with properties that can be tailored to suit particular design requirements. And because of the ease with which complex shapes can be manufactured, the complete rethinking of an established design in terms of composites can often lead to both cheaper and better solutions. So, in order to get the best quality characteristics, the material and machine parameters influencing the machining process need to be optimized. The design of experiment approach, notably Taguchi method, is suitable for optimization of single response only. In practice, multiple responses are desired to be simultaneously optimized. It is difficult to find a single optimal combination of process parameters for multiple performance characteristics since process parameters influence them differently. Hence, there is a need for a multiple response optimization method to arrive at the solutions to this problem. Classical methods for solving multiple objective optimization problem use weighted functions for transforming the multiple objectives into an equivalent single objective leading to trading off of responses. The best parameter combination may be far away from the real optimal parameters. Moreover, the classical methods fail when the function becomes discontinuous. To alleviate this problem, a number of multiple response optimization methodologies like fuzzy logic, grey relational analysis and artificial neural network have been proposed to machining of composites [60, 90-92]. Chen at al. [97] optimized the process parameters while machining tungsten in a wire electrical discharge machining set up using combined Taguchi's method with back-propagation neural network. Haq et al. [98] optimized multiple responses in drilling of AlSiC MMC by integrating Taguchi's method with grey relational analysis. Aggarwal et al. [99] optimized the machining parameters of CNC turned parts combining principal component analysis with Taguchi method. In most of the approaches, the responses are considered to be uncorrelated. In practice, the responses are not independent rather they are correlated and conflicting in nature. Therefore, it is vital to study the correlation of responses before applying any method for converting multiple responses into an equivalent single response. In this study, principal component analysis (PCA) is applied on responses to obtain uncorrelated principal components (PCs). Further, the experimental data are also subjected to uncertainty and impreciseness. Therefore, fuzzy inference system is adopted to convert multiple responses into a single response known as multi-performance characteristic index (MPCI) so that uncertainty and impreciseness can be taken into account [96]. The rule base for fuzzy inference system can be easily developed in practice using the expertise of shop floor managers or tool engineers. In recent times, a new trend has been introduced to hybridize the features of two or more than two techniques to take advantage of the potential of each technique and shrink their disadvantages. Such technique with combined features is called as hybrid modeling technique. So PCA-Fuzzy inference system is a hybrid optimization technique for multi-responses optimization.

2.5 Conclusion

Exhaustive literature survey focused into various past works carried in the production of MMCs. The investigations of several researchers have been thoroughly studied and their conclusive findings have been recorded concerning the processing and machining of composites through various routes. Powder metallurgy and Electro Discharge Machining are considered for the composite production. Machining parameters affecting quality characteristics in the machining process is thoroughly studied. Productivity is constantly a matter of concern with a high level of accuracy for any process; rather it is the driver of economic growth of industry. Therefore, it is always desirable to have machining with maximum MRR, minimal TWR and minimum surface roughness along with better circularity. At the end of this chapter various multi-responses optimization methods has been examined. A hybrid approach combining both Principal component analysis and Fuzzy inference system with Taguchi methodology is suggested to predict the optimal parameter setting for the machining process.

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CHAPTER-3

EXPERIMENTAL DETAILS

CHAPTER-3

EXPERIMENTAL DETAILS

3.1 Introduction

This chapter describes the experimental procedure adopted in the present project-work. A detailed report is also provided on the characterization of raw materials used for fabrication of the MMC test specimens. The chapter houses a description of the detailed step-wise methods adopted for fabrication of the test specimens, the thermal treatment imparted the Mechanical and electrical testing carried out. Micrographs are generated through Scanning Electron Microscopy for the detailed analysis of reinforcement distribution in the matrix. Then machining is performed on the prepared MMC to study the quality characteristics. For the sake of clarity and visual basics, photographs of equipments / instruments that have been used in this work are also presented according to their place of use.

3.2 Material

Commercial grade Aluminium alloy powders were obtained from Loba Chemie Pvt. Ltd., India. The SiC particulates were obtained from the market. The specifications/composition obtained is presented below.

3.2.1 Aluminium Alloy:

The aluminium alloy contains Al-99.7%, Fe-0.17%, Mg-0.0016%, Zn-0.0053%, Cu-0.00159% of other materials. And Particle sizes -120 mesh (~20 µm).

3.2.2 SiC particulates:

SiC_p is obtained from the open market with assay 99% (metal basis) and Particle size: 300 mesh (50 µm), 400 mesh (37 µm)

3.2.3 Pre-treatment of SiC particulates

The SiC_p is heated to a temperature of 700^0C in a muffle furnace (Wild Barfield furnace, max. temp. 1350^0C, Made in England) in the presence of air and kept at the temperature for sixty minutes prior to using it for fabrication of the MMC samples. This is done in order to form a thin layer of SiO_2 on the SiC_p surface to make it inert to aluminium so that the direct reaction between aluminium and SiC_p is avoided [100]. If SiC is used as a reinforcement in an Al alloy matrix containing less than 7% Si, then the Al from the matrix migrates to the SiC reinforcement and reacts with it, which otherwise would produce aluminium carbide and silicon following the reaction given as, $4Al + 3SiC \Leftrightarrow Al_4C_3 + 3Si$

Figure 3.1 Muffle furnace

3.3 Specimen fabrication

Based on the exhaustive literature survey, it is concluded that powder metallurgy method of the solid phase processing methods serves better than other process. Powder metallurgy (P/M) is one of the processing techniques adopted for silicon carbide reinforced aluminium composites because relatively lower temperatures (below melting point) are involved in P/M processing. Homogenous, high strength and net shape components of aluminum-silicon carbide composites can be produced through powder metallurgy (PM) route. The undesirable interfacial reactions and development of detrimental intermetallic phases are negligible in AlSiC composites as compared to the cast composites. Compared to fibrous composites, particulate composites offer improved ductility and reduced anisotropy in mechanical properties and hence, can be subjected to extrusion, forging and rolling. On a cost-benefit scale, the particulate composites are generally far superior. However, homogeneity, machinability, and interfacial reaction of the constituents represent the large problems pertaining to these composites.

3.4 Powder metallurgy method

The MMC test specimens are fabricated by powder metallurgy route using ball mill mixing, solid state sintering and heat treatment.

3.4.1 Mixing of powders

The MMC test specimens are fabricated by the powder metallurgy route adopting the usual mixing and solid state sintering. 90% and 85 % Aluminium powder and 10% and 15 % SiC_p by weight are mixed for fabricating the composite. 300 and 400 mesh SiC_p each of 10 and 15 % were weighted and mixed. Total four categories of mixture were prepared (90% Al+ 10 % SiC (300 mesh), 90% Al+ 10 % SiC (400 mesh), 85% Al+ 15 % SiC (300 mesh), 85% Al+ 15 % SiC (400 mesh)). Blending is carried out in ball planetary mill (Model-PULVERISETTE-5, Make-FRITSCH, Germany) shown in figure 3.2. It consists of two cylindrical containers of chrome steel inside which 10 balls made up of chrome steel of sizes 10 mm. The blending machine continues rotations for 3 lakh revolutions to reach a homogenous distribution of the reinforcement in the mixture.

Figure 3.2 Ball planetary mill

3.4.2 Compaction of the powder mix

About 10gms of the powder mixture was taken adopting a method of coning and quartering for compaction in a cold uniaxial press in a metallic die-punch arrangement.

3.4.3 Cold uniaxial pressing

The powder sample is pressed in the cold uniaxial pressing machine (Make-SOILLAB ,Type-Hydraulic) to render the green circular test samples of 25mm outer diameter applying a load of 18 ton, which accounted 3600 bar pressure. A stainless steel die of 25 mm internal diameter was used for this purpose. To allow the powder to flow freely and to prevent the specimen from sticking on to the walls, stearic acid was used as a lubricant that was applied to the walls of the die and punch. The pressing machine is shown in figure 3.3.

Figure 3.3 Cold uniaxial pressing machine

3.4.4 Sintering of the green samples

The green samples are carefully baked at an elevated temperature in a controlled atmosphere environment but just below the melting point of major constituent for a sufficient time. It is carried out in horizontal tubular furnace (Make-Naskar and Co., Type- Vacuum and Control Atmosphere) in an atmosphere of argon at pressure of 1 bar as shown in figure 3.4. A batch of eight samples from each of the two mixtures containing 10, 15 % SiC were sintered at two different temperatures 600 and 650^0 C respectively. The time of holding was one hour. The high temperature sintering process cause the aluminum surrounded by the oxide layer in the particle to melt and expand in volume to rupture the oxide envelope surrounding it and makes contact with melted aluminum leaking from nearby particles and welding take place. The oxide layer broke into small shell fragments impeded in the aluminum matrix restricting the movement of dislocation and increase strength. The presence of silicon carbide particles also hinders the aluminum melt from one particle to join melt from another. So increasing silicon carbide content increase the sintering temperature needed to achieve high strength composite. Then furnace is allowed to cool to room temperature for a span of 24 hours. Then, the pallets are removed from the furnace and kept in a desiccators containing concentrated H_2SO_4. The average diameter and thickness of pallets are 22 mm and 9 mm.

Figure 3.4 Horizontal tubular furnace

3.4.5 Heat treatment

Heat treatment refines the grain structure inside a material part, thus increasing its mechanical properties.

3.4.5.1. Quenching

The samples were then solution heat treated at 500 ^{0} C for one hour and then quenched in iced water. Quenching was carried in a heat treatment furnace (Local made) shown in figure 3.4.

Figure 3.5 Heat treatment furnace

3.4.5.2. Ageing

In order to prevent the initiation of natural ageing after this quench, all samples were artificial aged immediately after solution heat treatment. All samples were aged at 200^0 C for eight hour in a closed muffle furnace and left to cool in it. Muffle furnace is shown in figure 3.6.

Figure 3.6 Muffle furnace

The sintered samples prepared by the above discussed process are shown in Figure 3.7. These green samples are ready for further use. The properties of the samples were then measured by different measuring equipment and presented in Table 3.1.

Figure 3.7 Sintered samples

3.5 Results & discussions

3.5.1 XRD analysis

To confirm the certainty of the constituents present in the blended powder of the specimen, supplied matrix element (aluminum) and reinforcement element (silicon carbide), X-Ray diffraction analysis is carried out using XRD instrument supplied by XRD -PHILIPS Analytical Ltd. PW 3040 as shown in figure 3.8. After the XRD analysis, the peaks obtained is shown in Figure 3.9 confirms the presence of only two phases viz., Al and SiC crystals. The data obtained from XRD of above elements (counts at different angles, 2θ and d-spacing, $\overset{0}{A}$) are analyzed using Xpert Highscore software (Philips). From the XRD graph (Figure 3.9), it is shown that aluminium is 99.7% pure and the rest contains aluminium alloys like aluminium silicon, aluminium manganese and aluminium titanium. XRD test is also carried out on silicon carbide of both mesh sizes. It is found that SiC contains mostly moissanite-6H i.e. SiC and very little traces of Paladium Oxide and $Al_2Si_3O_{12}$. Again XRD analysis is performed to confirm the constituents present in the blended powder of the specimen. It was found that the specimen was free from chrome steel crystals expected from blending in a chrome steel crucible. These results confirm the suitability of the sample pallets in respect of uniform distribution of particles and confirm that they are precisely accurate for further analysis.

Figure 3.8 XRD instrument

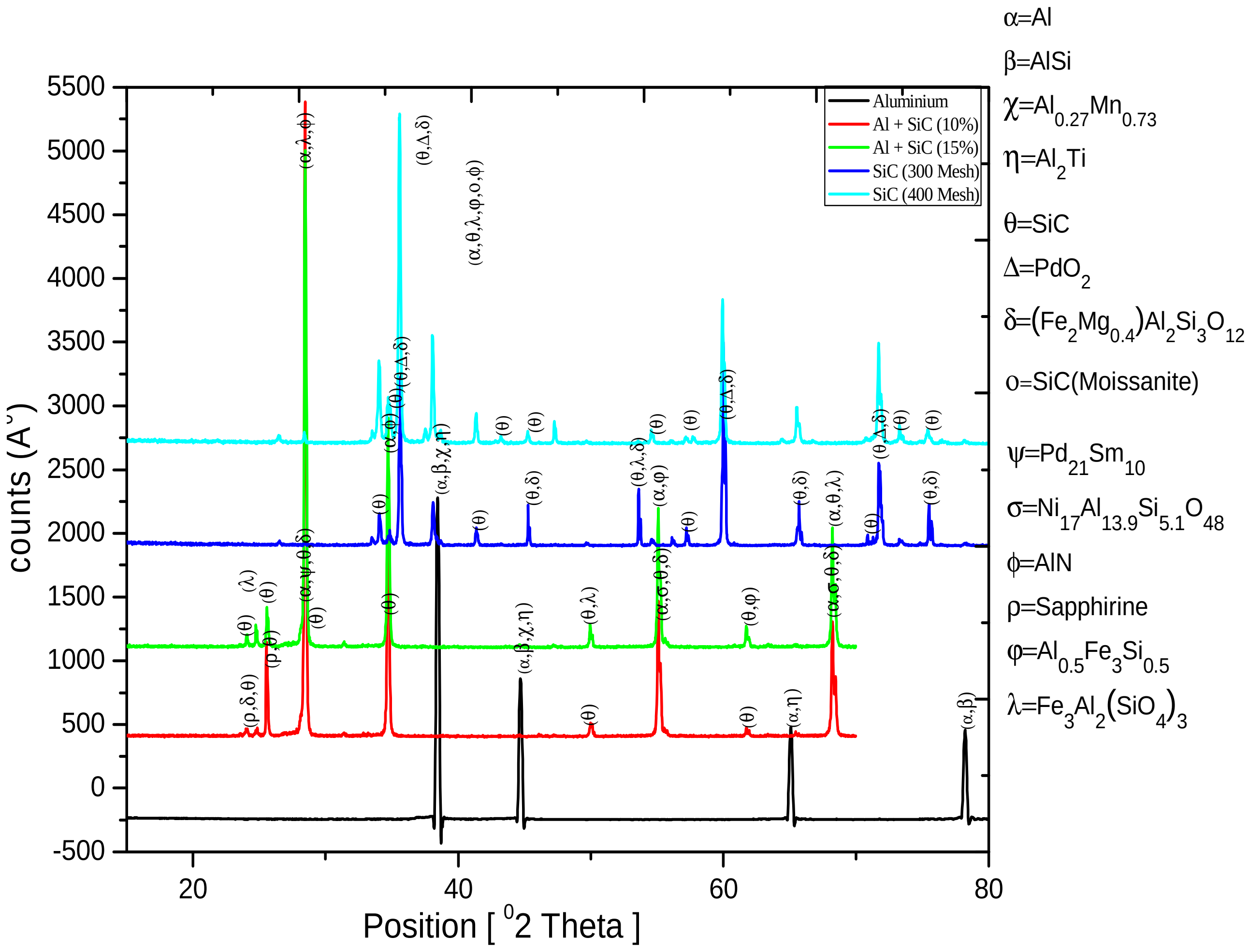


Figure 3.9 The XRD graphs

3.5.2 Density

The actual densities of the samples are obtained through water immersion method shown in Table 3.1. From Table 3.1, it is observed that maximum of 67.24% increase in density occurs after sintering the green samples due to filling up of the voids between particles with melted aluminum. Theoretically, the densities of the composites are measured using the following relation.

$$\rho_C = \frac{1}{\left(\left(W_{Al}/\rho_{Al}\right)+\left(W_{SiC}/\rho_{SiC}\right)\right)} \qquad (4.1)$$

where

ρ_C - Composite density, g/mm^3

W_{Al} - Weight fraction of aluminium

ρ_{Al} - Density of aluminium (0.00262 g/mm^3)

W_{SiC} - Weight fraction of silicon carbide

ρ_{SiC} - Density of silicon carbide (0.0032 g/mm^3)

Using above equation, the theoretical density of the MMC is found to be 0.00268 g/mm^3. The average actual density is found to be 0.00230g/mm^3. The difference in density is attributed to presence of voids in the samples.

3.5.3 Hardness

Hardness of the green and sintered samples is measured by the equipment Vickers hardness measuring machine (Leco Vickers Hardness Tester, USA Model: LM 2481T) in figure 3.10.From Table3.1, it is observed that hardness increases by at least 40% after sintering. The average hardness for samples is found to be 56.61 and 73.08 VHN for SiC weight percentage of 10 and 15 respectively whereas hardness for aluminiumis 15 VHN. Figure 3.11 shows that average hardness of samples increases as mesh size increases and wt. % of SiC increases. However, mesh size of SiC causes significant improvement in the hardness of the MMC.

Figure 3.10 Vickers hardness measuring machine

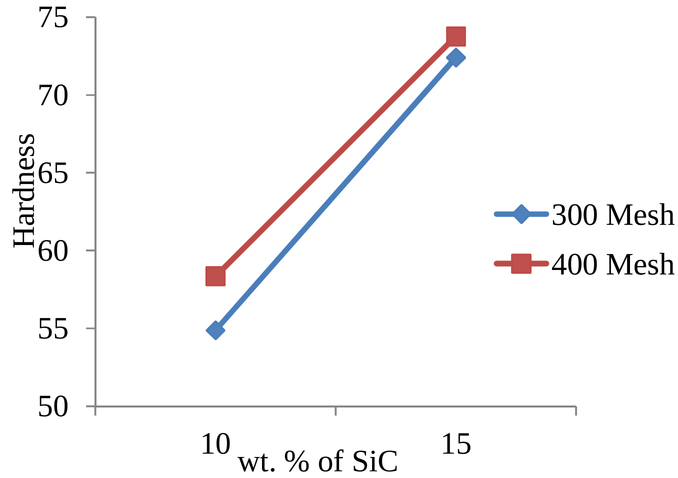


Figure 3.11 Variation of hardness with % of SiC

3.5.4 Conductivity

Conductivity of MMC is measured by digital electrical conductivity measuring device (Sigmascope SMP 10) as in Figure 3.12 using aluminium plating at room temperature. From Table 3.1, it can be noticed that conductivity decreases when silicon carbide percentage in the sample increases from 10 to 15% due to resistive nature for electricity conduction of SiC_p. However, the conductivity of the samples is enough to facilitate electrical discharge machining on samples because the machining process needs minimum conductivity of work piece as 0.01 S/cm [101].

Figure 3.12 Digital electrical conductivity measuring device

Table 3.1 Properties of the samples

		Density (g/mm^3)			Hardness (VHN)			
% SiC	Mesh Size	Before Sintering	After Sintering & HT	% increase	Before Sintering	After Sintering & HT	% increase	Electrical Conductivity (S/cm)
10	300	0.001801	0.00182	1.05	47.6	58.9	23.74	1.11
10	300	0.001745	0.00178	2.00	48.7	51.0	4.72	1.11
10	300	0.001730	0.00186	7.51	48.1	50.3	4.57	1.25
10	300	0.001716	0.00185	7.80	45.3	59.3	30.91	1.11
10	400	0.001743	0.00248	42.28	53.8	58.5	8.74	1.25
10	400	0.001749	0.00221	26.35	50.3	61.4	22.07	1.43
10	400	0.001728	0.00280	62.03	51.4	53.0	3.18	1.25
10	400	0.001726	0.00230	33.25	51.9	60.5	16.57	1.25
15	300	0.001762	0.00290	19.75	57.2	68.3	19.41	1.00
15	300	0.001773	0.00254	61.30	58.1	73.2	26.00	0.91
15	300	0.001752	0.00244	21.57	57.8	73.1	26.47	0.91
15	300	0.001768	0.00223	34.61	60.1	75.0	24.79	1.00
15	400	0.001734	0.00211	67.24	60.6	76.5	26.24	0.91
15	400	0.001726	0.00286	47.16	58.5	71.7	22.56	1.00
15	400	0.001720	0.00213	41.86	59.8	74.2	24.08	0.91
15	400	0.001710	0.00238	30.40	61.8	72.6	17.48	1.11

HT- Heat treatment

3.5.5 Microstructure analysis

Microstructure examinations are carried out to investigate of distribution of the silicon carbide particles in the composite. Samples having 10 and 15 weight percentage of silicon carbide are examined at both green and sintered state. The samples are polished using emery paper (1000 and 1500 grit size) and finally etched using acetone. The microstructures of samples are studied using a Scanning Electron Microscope (SEM) (JEOL JSM 6480 LV) shown in Figure 3.13.

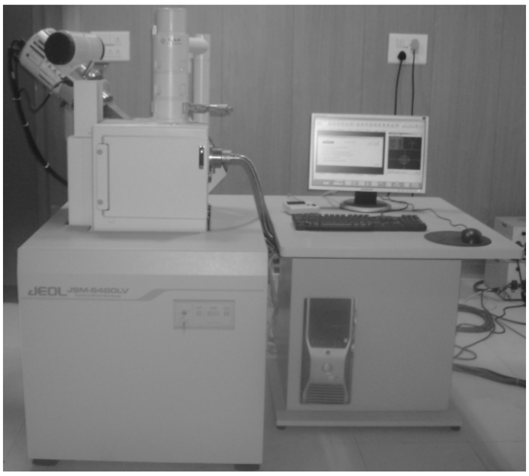
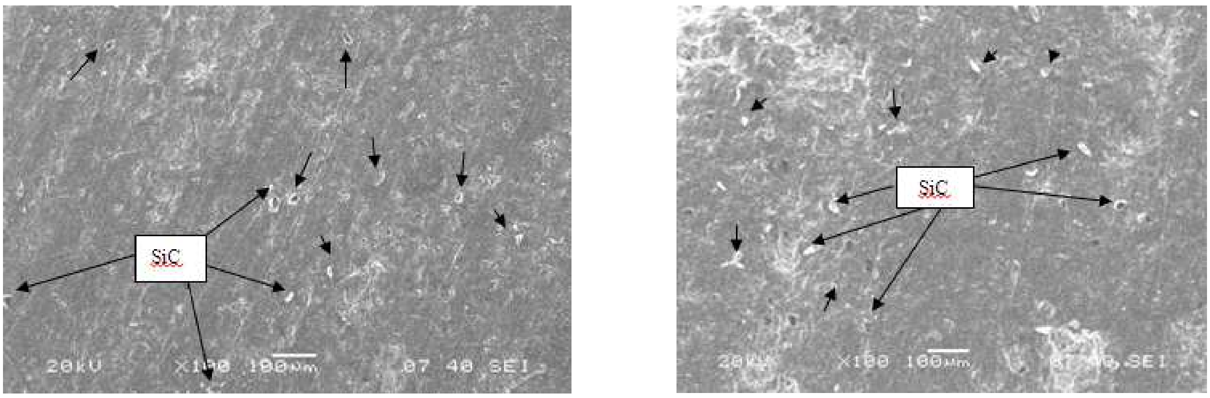


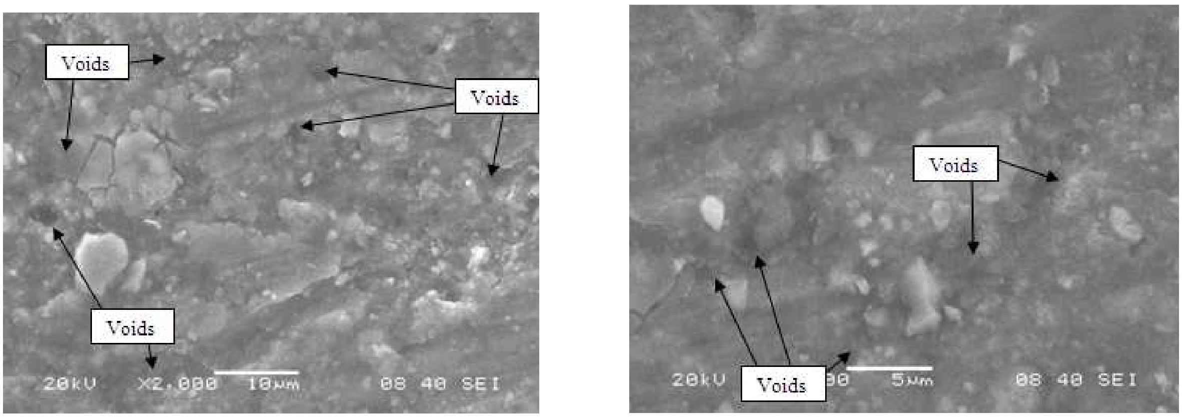
Figure 3.13 Scanning Electron Microscope

Micrographs of samples taken before sintering (green samples) are shown in Figure 3.14. It is observed that silicon carbide particles are homogeneously distributed in the matrix. Some clustering of the reinforcement is found in both the micrographs and increases as the percentage of reinforcement and mesh size increases. Figure 3.15 shows the micrographs of the sintered samples. It can be observed that silicon carbide particles are covered by melted aluminum particles. In spite of compaction and sintering, presence of voids in the matrix cannot be avoided. More number of voids of larger size is observed in the samples of 10% weight percentage of silicon carbide as compared to 15% weight percentage of silicon carbide. It was also observed that voids are more pronounced when size of silicon carbide is decreased.



(a) (b)

Figure 3.14 Micrographs showing the distribution of the reinforcement in the composite (green samples) (a) 10% SiC (300 Mesh size) (b) 15% SiC (400 Mesh size)



(a) (b)

Figure 3.15. Micro-graphs showing aluminium and voids in the composite (sintering samples) (a) 10% SiC (300 Mesh size) (b) 15% SiC (400 Mesh size)

3.6 Design of Experiments

A commonly use approach in scientific and engineering investigation is to study one factor at a time or study several factors one at a time. This approach has inherent disadvantages like, more experimental runs are require for the precision in effect estimation, factor interaction effects cannot be studied, conclusions are not general and may miss the optimal settings of factor. To overcome this problem design of experiment (DOE) is a scientific approach to effectively plan and perform experiments, using statistics and are commonly used to improve the quality of a products or processes. Such methods enable the user to define and study the effect of every single condition possible in an experiment where numerous factors are involved [102-103]. EDM is such a process in which a number of control factors collectively determine the output responses in other words quality characteristics. Hence, in the present work one statistical technique called Taguchi method is used to optimize the process parameters leading to the improvement in quality characteristics of the part under study.

The most important step in the DOE lies in the selection of the control factors and their levels. EDM process has large number of process related parameters which are defined below. Based on initial trials and exhaustive literature review [85-89] four machining parameters namely, discharge current (Ip), pulse-on-time (Ton), duty cycle (τ) and flushing pressure (Fp) are identified and two material parameters such as mesh size and wt% of SiC are treated as controllable parameters. The machining parameters are set at four levels whereas material parameters are set at two levels. The details of parameters and their levels are shown in Table 3.2 as significant factors and hence are selected to study their influence on output responses.

Table 3.2 Control parameters and their levels.

Symbol	Control parameters	Levels			
		1	2	3	4
A	Discharge current (A)	1	3	5	7
B	Pulse-on-time (μS)	100	200	300	400
C	Duty cycle (%)	80	85	90	95
D	Flushing pressure (bar)	0.9806	1.9613	2.1419	3.9226
E	SiC (wt%)	10	15		
F	Mesh size(particle size in micron)	300 (50)	400 (37)		

3.7 Taguchi experimental design

Taguchi experimental design that extensively uses orthogonal arrays is an efficient tool for improving process/product quality with relatively less number of experimental runs. The method can optimize performance characteristics through determination of best parameter settings and reduces the sensitivity of the system performance to sources of variation. Orthogonal arrays provide a set of well-balanced experiments with less number of experimental runs. A mixed orthogonal array is formed by taking four machining parameters each at four levels and two material parameters each at two levels. The appropriate array for this case is L_{16} Orthogonal array is shown in Table 3.3.

Table 3.3 L_{16} Orthogonal array

Exp. No	Factors					
	A	B	C	D	E	F
1	1	1	1	1	1	1
2	1	2	2	2	1	2
3	1	3	3	3	2	1
4	1	4	4	4	2	2
5	2	1	2	3	2	2
6	2	2	1	4	2	1
7	2	3	4	1	1	2
8	2	4	3	2	1	1
9	3	1	3	4	1	2
10	3	2	4	3	1	1
11	3	3	1	2	2	2
12	3	4	2	1	2	1
13	4	1	4	2	2	1
14	4	2	3	1	2	2
15	4	3	2	4	1	1
16	4	4	1	3	1	2

3.8 Electrical discharge machining process

The study intends to investigate the effect process parameters such as discharge current (Ip), pulse-on-time (Ton), duty cycle (τ) and flushing pressure (Fp) on material removal rate (MRR), tool wear rate (TWR), surface roughness (R_a) and circularity (r_1/r_2). The equipment used to perform the experiments is an Electronica Electraplus PS 50ZNC Die Sinking Fuzzy Logic based Electrical Discharge Machine shown in Figure 3.16. Commercial grade EDM oil (specific gravity = 0.763, freezing point= 94˚C) is used as dielectric fluid. A lateral flushing system is employed for effective flushing of machining debris from the working gap region. To get more accurate results, each experiment is conducted for one hour. The work piece material used is aluminium silicon carbide metal matrix composite. Straight polarity is adopted due to high MRR. A cylindrical copper tool with a diameter of 12 mm is used as a tool electrode (negative polarity) and workpiece material (positive polarity). Density of copper tool taken is 0.00896 kg/m^3 Shown in Figure 3.17. The photos of the machined (drilled) AlSiC MMCs are shown in Figure 3.18. The MRR is calculated using the volume loss from the work piece as cubic millimeter per minute. During the electric discharge, some of the discharge energy applied to the tool produces a crater in the tool material. TWR is expressed as the volumetric loss of tool per unit time. The weight loss is measured by an electronic balance weight measuring machine (Sansui (Vibra), Shinko Denshi Co. Ltd. Made in Japan) with a least count of 0.001g and shown in Figure 3.19.

Figure 3.16 Electrical Discharge Machine

Figure 3.17 Copper tool (electrode)

Figure 3.18 Machined AlSiC composites

Figure 3.19 Electronic balance weight measuring machine

3.8.1 Material removal rate (MRR)

MRR is expressed as,

$$MRR = \frac{W_i - W_f}{\rho_w T} \tag{3.2}$$

where W_i= initial weight of work piece, W_f = final weight of work piece, ρ_w= density of work piece material, T= machining time (60 minutes).

3.8.2 Tool wear rate (TWR)

TWR is expressed as,

$$TWR = \frac{T_i - T_f}{\rho_t T} \tag{3.3}$$

where T_i= initial weight of the tool, T_f= final weight of the tool, and ρ_t= density of tool

3.8.3 Surface roughness

To determine the effect of the EDM process on the surface roughness (R_a) of the tool steel, the surface profiles of the EDM specimens are measured by using a portable stylus type profilometre like Talysurf (Taylor Hobson) shown in Figure 3.20. Surface roughness can be expressed as, $R_a = \frac{1}{L}\int |y(x)|dx$, where L is the sampling length, y is the profile curve and *x* is the profile direction. The sampling length is taken as 0.8 mm. Surface roughness measurements of electrical discharge machined surfaces were taken to provide quantitative evaluation of the effect of EDM parameters on surface finish as it provides better surface finish than other non-conventional machining process.

Figure 3.20 Stylus type profilometre

3.8.4 Circularity

Circularity is one of the important metrological parameters used to control the roundness of circular parts or features. Due to continuous sparking and high amount of heat content in the electrode, the work piece material undergoes overcuts. As the tool is of cylindrical shape, the work piece encounters circularity error. The circularity of the hole is measured by using the ratio of minimum (r_1) to maximum (r_2) Feret's diameters of the hole. The diameters are measured using optical microscope (RADIAL INSTRUMENT with Samsung camera setup, 45-X magnification) shown in Figure 3.21. Feret's diameter is obtained by joining tangents to the maximum points of the surface as shown in Figure 3.22.

Figure 3.21 Optical microscope

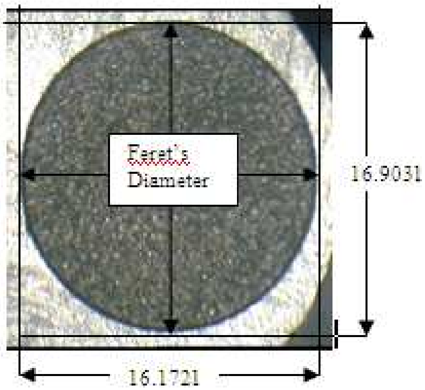


Figure 3.22 Feret's diameters

3.9 Conclusion

This chapter summarizes the materials and details of Experimental Processes and procedures as adopted in the present project work, along with details of manufacturing and testing equipments.

CHAPTER-4

METHODOLOGY

CHAPTER-4

METHODOLOGY

4.1 Introduction

In the simplest case, an optimization problem consists of maximizing or minimizing a real function by systematically choosing input values from within an allowed set and computing the value of the function. The generalization of optimization theory and techniques to other formulations comprises a large area of applied mathematics. An amazing variety of practical problems involving decision making (or system design, analysis, and operation) can be cast in the form of a mathematical optimization problem, or some variation such as a multi response optimization problem. Indeed, mathematical optimization has become an important tool in many areas. It is widely used in engineering, in electronic design automation, automatic control systems, and optimal design problems arising in civil, chemical, mechanical, and aerospace engineering. Since the late 1940s, a large effort has gone into developing algorithms for solving various classes of optimization problems, analyzing their properties, and developing good software implementations. In this contest, the task is to find a model, from a family of potential models, which best fits some observed data. Here the variables are the parameters in the model. In order to determine the factor level settings that optimize the performance of the quality characteristics in a single setting, a hybrid optimization technique namely principal component analysis (PCA) coupled with fuzzy inference system are used for combining multiple responses into a single response known as multi-response performance characteristics index (MPCI). Finally, empirical relationship between process parameters and MPCI is derived using Taguchi methodology. To check the soundness of this hybrid optimization technique, another solo optimization technique called weighted principal component analysis (WPCA) is used. In this context optimal settings from both the techniques are compared and analyzed. Development of a valid model helps to search the optimization landscape to find out best possible parametric combination resulting best quality characteristics, which has not been explored during experimentation.

4.2 Taguchi method

In determining the effectiveness of a design, we must develop a measure that can evaluate the impact of the design parameters on the output quality characteristics. This measure is introduced by Dr. Genichi Taguchi and called "*Taguchi's philosophy*". It is an efficient tool for the design of high quality manufacturing system. It is a widely accepted methodology for contemporary experiment design. The Taguchi method can optimize performance characteristics through the settings of process parameters and reduce the sensitivity of the system performance to sources of variation. As a result, the Taguchi method has become a powerful tool in the design of experiment methods.

Taguchi proposes a three-stage design operation to determine the nominal values for relevant parameters in the process: system design, parameter design and tolerance design. In this study parameter design is followed. Parameter designs involve finding the optimal settings of the process in order to minimize performance variability. Taguchi defines a performance measure known as signal-to-noise (S/N) ratio and tries to select the parameter levels that maximize the ratio. The term signal represents the square of the mean value of the quality characteristic, whereas noise is a measure of the variability (as measured by the variance) of the characteristic [104].

However, Taguchi method is concerned with the optimization of a single performance characteristic. Handling the more demanding multiple performance characteristics are still an interesting research problem.

4.2.1 Performance evaluation

In order to evaluate the optimal parameter setting, Taguchi method uses a statistical measure of performance called signal-to-noise (S/N) ratio that takes both the mean and the variability into account. Formerly, The S/N ratio was an electrical engineering concept defined as the ratio of signal power to noise power corrupting the signal. Taguchi expands this conception to the engineering system design area. The philosophy of Taguchi methods stresses that every engineering system is a man-made system, which employs energy transformation to convert input signal(s) into specific intended function. The ratio depends on the quality characteristics of the product/process to be optimized. The optimal setting is the parametric combination that results in highest S/N ratio. Usually, there are three categories of signal-to-noise ratios such as lower-the-better (LTB), the higher-the-better (HTB), and nominal-the-best (NTB). In this study, four responses such as material removal rate (MRR), tool wear rate (TWR), surface roughness (Ra) and circularity of machined component are considered. Two responses like surface roughness and tool wear rate are to be minimized whereas two responses like material removal rate and circularity are to be maximized. Therefore, HTB and LTB categories of S/N ratios are dealt here.

The higher-the-better (HTB) S/N ratio is given by

$$\text{HTB S/N Ratio} = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right) \tag{4.1}$$

The lower-the-better (LTB) S/N ratio is given as

$$\text{LTB S/N Ratio} = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}y_i^2\right) \tag{4.2}$$

where y_i denotes the value of the response for replicate i and n is the number of replicates. The S/N ratio measures the level of system performance and the higher value gives more robustness of the system.

However, Taguchi method is concerned with the optimization of a single performance characteristic. Handling the more demanding multiple performance characteristics are still an interesting research problem. Researchers have suggested different multi-response optimization techniques but some proposed methods increases uncertainties due to unknown correlations among the objectives or multi performance characteristics (MPCs). To solve the correlation problem, PCA is an advisable statistical technique to examine the correlation within the MPCs. A new set of uncorrelated data of MPC, called principal components, could be derived by PCA to explain the variance by generating principal component scores. Now it is fruitful to apply any multi-objective optimization methods to the process by converting the multi-responses into a single index i.e. multi-response performance characteristic index (MPCI). Fuzzy logic and weighted principal component analysis will be used to calculate the MPCI value in two different ways. Then, Taguchi method can be used to analyze MPCI to obtain best parameter setting which simultaneously optimizes multiple responses.

4.3 Principal component analysis

In dealing with multiple responses, care must be taken to uncorrelate multi-response data so that misleading interpretations during data analysis can be avoided. Independent modeling of each response variable does not take into account the relationships or correlations among the variables. The basic problem relates to the fitting of multi-response models while ignoring the three kinds of dependencies that can occur: (i) dependence among the errors, (ii) linear dependencies among the expected value of the responses and (iii) linear dependencies in the original data. To overcome these difficulties, a strategy based on multivariate statistics for summarizing and reducing the dimensionality of the data can be employed [105]. Such a strategy is the principal component analysis (PCA).

Principal component analysis was invented by Karl Pearson in 1901 and developed into a computational method by Hotelling in 1933 [106, 107]. According to hair et al. [108] principal component analysis is a multivariate analysis method widely used for data reduction. It involves a mathematical procedure that reduces the dimensions of a set of variables by re-constructing them into uncorrelated combinations. PCA is a multivariate statistical method, which allows the original initial variables to transform into another dimensional set of uncorrelated variables called principal components (PCs). The principal components are transformed by calculating the eigenvectors of the covariance matrix of the original inputs. The transformed variables are ranked according to their variance reflecting a decreasing importance in order to capture the whole information content of the original dataset. The PCs, which are expressed as linear combinations of the original variables, are orthogonal to each other and can be used for the effective representation of the system under investigation. To keep some observations or variables from discriminating the calculations, the data are normalized prior to finding the principal components. Such data preprocessing can avoid the influences of the units and the relative spread of the data used for evaluating the multiple performance characteristics. Normalization of the data provides fair information for determining the optimal levels of process parameters. The original data are converted to a range 0 to 1 with 1 counting the best performance and 0 the worst. The normalization procedure for higher-the-better characteristic is given in equation:

$$x_i^*(j) = \frac{x_i - [\min(x_i(j))]}{[\max(x_i(j))] - [\min(x_i(j))]} \tag{4.3}$$

The normalization procedure for lower-the-better characteristic is shown in equation (4.4).

$$x_i^*(j) = \frac{[\max(x_i(j))] - x_i(j)}{[\max(x_i(j))] - [\min(x_i(j))]} \tag{4.4}$$

where $x_i^*(j)$ denotes the value of the response j after normalization (In this study, the S/N ratio values for four responses such as MRR, TWR, Ra, and circularity represent responses j=1, 2, 3, and 4 respectively) and i denotes the experiment number.

In general PCA follows some basic steps to calculate Principal components and the steps involved are:

Step-1: The original multi-response array

In general, for i=1,2,..,m experiments and j=1,2,..,n responses, the original multiple response array $x_i(j)$ for S/N ratio X is given as

$$X = \begin{bmatrix} x_1(1) & x_1(2) & \cdots & x_1(n) \\ x_2(1) & x_2(2) & \cdots & x_2(n) \\ \vdots & \vdots & \cdots & \vdots \\ x_m(1) & x_m(2) & \cdots & x_m(n) \end{bmatrix}$$

Step-2: Normalizing the response

For normalization of the responses, higher-the-better criterion is selected as stated in equation (3) because higher S/N ratio of response is desirable.

$$X^* = \begin{bmatrix} x_i^*(1) & x_1^*(2) & \cdots & x_1^*(n) \\ x_i^*(1) & x_2^*(2) & \cdots & x_2^*(n) \\ \vdots & \vdots & \cdots & \vdots \\ x_m^*(1) & x_m^*(2) & \cdots & x_m^*(n) \end{bmatrix}$$

X^* is the normalized response array

Step-3: Correlation coefficient array

The correlation coefficient array of the normalized response array is evaluated as follows

$$R_{jl} = \left(\frac{Cov\left(x_i^*(j), x_i^*(l)\right)}{\sigma_{x_i^*(j)} \times \sigma_{x_i^*(l)}} \right) \tag{4.5}$$

where j=1,2,..n and l =1,2,..n

$\operatorname{cov}\left(x_i^*(j), x_i^*(l)\right)$ is the covariance of sequences $x_i^*(j)$ and $x_i^*(l)$, $\sigma_{x_i^*(j)}$ and $\sigma_{x_i^*(l)}$ are standard deviation of sequences, $x_i^*(j)$ and $x_i^*(l)$ respectively.

Step-4: Determination of eigenvalues and eigenvectors

The eigenvalues and eigenvectors are calculated from the correlation coefficient array,

$$(R - \lambda_k I_m)V_{ik} = 0 \tag{4.6}$$

where λ_k are eigenvalues, k is the number of principal components extracted, and

$$\sum_{k=1}^{n} \lambda_k = n, \;\; k = 1, 2, \cdots n$$

$V_{ik} = [a_{k1}\; a_{k2} \cdots a_{kn}]^T$: Eigenvectors corresponding to the eigenvalues λ_k

Step-5: Evaluating the principal components

The uncorrelated principal components (PCs) are given as

$$Y_{mk} = \sum_{i=1}^{n} X_m^*(i) \cdot V_{ik} \tag{4.7}$$

The PCs are created in order of decreasing variance and so the first principal component, Y_{m1} accounts for most variance in the data. The components with an eigenvalue greater than one are chosen to replace the original responses for further analysis [105, 109]. Still, PCA is not able to give a final solution which could be analyzed through Taguchi method. To optimize these principal component scores, fuzzy multiple attribute decision making process could be best chosen to reduce uncertainties and impreciseness. Using fuzzy logic analysis, multi-responses could be easily transformed into a single value of multi-performance characteristic indices (MPCIs) [110]. Then, Taguchi method can be used to analyze MPCI to obtain best parameter setting which simultaneously optimizes multiple responses.

4.4 Fuzzy inference system

Fuzzy sets and systems are introduced by Prof. Lotfi A. Zedah in 1965. According to him, *"A fuzzy set is a class of objects with a continuum of grades of membership. Such a set is characterized by a membership (characteristics) function which assigns to each object a grade of membership ranging between zero and one. The notations of inclusion, union, intersection,* *complement, relation, convexity, etc., are extended to such sets, and various properties of these notations in the context of fuzzy sets are established. In particular, a separation theorem for convex fuzzy sets is proved without requiring that the fuzzy sets be disjoint"* [111].

Fuzzy inference is a mathematical theory of inexact reasoning, which allows the human reasoning process to be modelled in linguistic terms [112]. It is highly suitable for defining the relationship between system inputs and desired outputs. Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. Fuzzy controllers and fuzzy reasoning have found particular applications in vary complex industrial systems which cannot be modeled precisely even under a variety of assumptions and approximations. A fuzzy system mainly composed of a fuzzifier, an inference engine, a knowledge base and a defuzzifier. The fuzzifier first uses membership functions to convert the crisp inputs into fuzzy sets, and then the inference engine performs a fuzzy reasoning on fuzzy rules to generate fuzzy values. Then the defuzzifier converts these values into crisp outputs.

Block diagram of a typical fuzzy logic system is presented in Figure 4.1. As outlined in Figure 1, a fuzzy rule based system consists of four parts: fuzzifier, knowledge base, inference engine and defuzzifier. These four parts are described below:

- *Fuzzifier*: The real input (PCs) in crisp form which contains precise information about the specific parameter is applied to the fuzzzifier. The fuzzifier converts this precise quantity to the form of imprecise quantity like 'large', 'medium', 'high' etc. with a degree of belongingness to it. Typically, the value ranges from 0 to 1.
- *Knowledge base*: The main part of the fuzzy system is the knowledge base in which both rule base and database are jointly referred. The database defines the membership functions of the fuzzy sets used in the fuzzy rules whereas the rule base contains a number of fuzzy IF-THEN rules.
- *Inference engine*: The inference system or the decision-making unit performs the inference operations on the rules. It handles the way in which the rules are combined.
- *Defuzzifier*: The output generated by the inference block is always fuzzy in nature. A real world system will always require the output of the fuzzy system to the crisp or in the form of real output. The job of the defuzzifier is to receive the fuzzy input and provide real world output. In operation, it works opposite to the input block.

In general two most popular fuzzy inference systems are available: Mamdani fuzzy model and Sugeno fuzzy model. The selection depends on the fuzzy reasoning and formulation of fuzzy IF-THEN rules. Mamdani fuzzy model is based on the collections of IF-THEN rules with both fuzzy antecedent and consequent predicts. The benefit of this model is that the rule base is generally provided by an expert and hence to a certain degree, it is translucent to explanation and study. Because of its ease, Mamdani model is still most commonly used technique for solving many real world problems [113, 114].

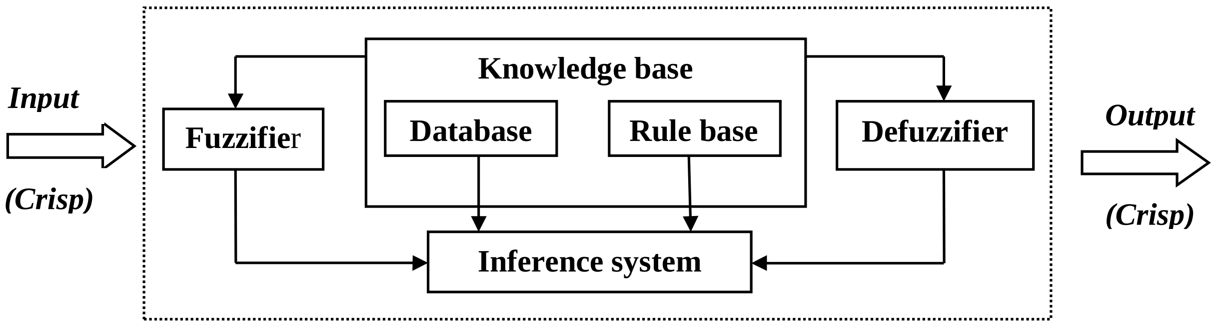


Figure 4.1 Structure of fuzzy rule based system

In the present study, an attempt is made to use fuzzy system (Mamdani) to estimate the MPCI when PCs are given as inputs to the system. The given model was a MISO (Multi Input and Single Output) model. The first step in system modeling is the identification of input and output variables called the system's variables. Only those inputs that affected the output to a large extent were selected. The number of input variables (PCs) obtained in PCA are labeled as PC_1, PC_2, PC_3….etc. are used as inputs. In three inputs (PCs) and one output (MPCI) system, both the inputs and the output are taken in the form of linguistic format. A linguistic variable is a variable whose values are words or sentences in a natural or man-made language. For example, PC_1 = {small, medium, large}, PC_2 = {small, medium, large}, and PC_3 = {small, medium, large). The output variable (MPCI) is similarly divided into MPCI = {small, small-medium, medium, medium-large, large}. Linguistic values are expressed in the form of fuzzy sets. A fuzzy set is usually defined by its membership functions, which define the degree of membership of an object in a fuzzy set [115]. Fuzzy values are determined by the membership functions,. However so far there has been no standard method for choosing the proper shape of the membership functions for the fuzzy sets of the control variables. Trial and error methods are usually employed. In general, triangular membership functions are used to normalize the crisp inputs because of their simplicity and computational efficiency. The triangular membership function as described in equations 4.8 is used to convert the linguistic values in the range of 0 to 1.

$$\text{triangle}\,(x;a,b,c)=\left\{\begin{matrix} 0, & x\le a \\ \dfrac{x-a}{b-a}, & a\le x\le b \\ \dfrac{c-x}{c-b}, & b\le x\le c \\ 0, & c\le x \end{matrix}\right\} \tag{4.8}$$

where a, b, c, d are the parameters of the linguistic value and x is the range of the input parameters. In this proposed model, each input has three triangular membership functions, where the output of the proposed model has five triangular membership functions.

The relationship between input and the output are represented in the form of IF-THEN rules. Let the 1st input (PC_1) is taken as P, the 2nd input (PC_2) is taken as Q, the 3rd input (PC_3) is taken as R and the output (MPCI) is taken as S. As per the fuzzy systems, the inputs ‘P’, ‘Q’ and ‘R’ has three membership functions each, hence 27 (3^3) rules can be made. In Mamdani fuzzy model, Max-Min inference was applied. The rules of the Mamdani fuzzy system are generated in the following ways:

R_1: IF P is P_1 = *Small* AND Q is Q_1 = *Small* AND R is R_1 = *Small* THEN MPCI(S) is S = S_1 = *Small.*

R_2: IF P is P_1 = *Small* AND Q is Q_1 = *Small* AND R is R_2 = *Medium* THEN MPCI (S) is S = S_1 = *Small*.

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R_{27}: IF P is P_3 = *Large* AND Q is Q_3 = *Large* AND R is R_3 = *Large* THEN MPCI (S) is S = S_5 = *Large.*

where P_1, P_2, P_3; Q_1, Q_2, Q_3; R_1, R_2, $R_3$are the linguistic parameters or membership functions of the inputs (P,Q and R) and S_1,S_2,….S_5 are the membership function of output (S).

In this proposed model, centriod of area (COA) method of defuzzification is used for determining the output as expressed in equation 4.9.

$$\text{Centriod of area } z^{COA} = \frac{\int_z \mu A(z) z dz}{\int_z \mu A(z) dz} \tag{4.9}$$

where$\mu A(z)$ is the membership value of set A and z is the variable.

The yielded value is the final crisp output value, which is obtained from the input variables. This crisp value is the MPCI, Which is further analyzed through Taguchi method to get the final optimal setting of the parameters. Finally, with the application of ANOVA (Analysis of Variance), significant factors in this quality index and their contribution percentage for total variation in MPCI can be obtained.

4.5 Weighted principal component analysis

To check the correctness of the PCA-Fuzzy based hybrid approach stated above, a method called weighted principal component (WPCA) is used [116]. In order to determine the optimum factor level setting that maximizes the performance of the quality characteristics in a single setting, weighted principal component analysis is applied for combining multiple responses into a single response known as MPCI.

This WPCA method follows the same steps as like PCA to calculate the principal components/principal component scores (PCs). In addition to this, it uses the variance (proportion explained) to calculate the MPCI without following to the complex fuzzy inference system like in the hybrid approach. The analysis combines the variables that account for the largest amount of variance to form the first principal component. The second principal component accounts for the next largest amount of variance, and so on until the total sample variance is combined into component groups. In a multiple responses case, the responses need to be converted into an equivalent single response for analysis purpose.

For calculation of weighted principal components, the initial step is to calculate the principal components (PCs). The PCs are calculated as per the steps prescribed in PCA. Principal components are independent (uncorrelated) of each other. Simultaneously, the explained variance of each principal component for the total variance of the responses is also obtained. Next, in weighted principal component method, all principal components will be used; thus the explained variance can be completely explained in all responses. Since different principal components have their own variance to account for the total variance, the variance of each principal component is regarded as the individual priority weight [113]. Because these principal components are independent to each other, an additive model can be developed by simply adding all principal components to represent multi-response performance characteristic index (MPCI). Therefore, MPCI is given as:

$$MPCI = \sum_{k=1}^{n} Y_{mk} W_k \tag{4.10}$$

where Y_{mk} is the uncorrelated Principal components and W_k is the weight of *k*th principal components. The weighted principal component analysis provides weights (Variance explained by each component) for each principal component to be extracted from data rather than restoring arbitrary and ambiguous method of assigning weights for conventional multi-responses into equivalent single responses (MPCI). The larger the MPCI is the higher the quality. The MPCI is further analyzed by Taguchi method and optimal parameter settings are obtained. Finally, with the application of ANOVA (Analysis of Variance), significant factors in this quality index and their contribution percentage for total variation in MPCI can be obtained.

4.6 Conclusion

In this present work, two multi-response optimization methods are proposed. The first one a hybrid approach combining Principal component analysis with Fuzzy inference system (PCA-Fuzzy) and another is Weighted Principal Component Analysis (WPCA) in combination with Taguchi's robust design methodology separately. The PCA-Fuzzy has been recommended to optimize the quality indices by uncorrelating them. This method is quite practical as it uses expert proposed rules. Based on variance; treated as individual response weights, WPCA can combine individual principal components into a single multiresponse performance characteristics index MPCI to be taken under consideration for optimization. This is really helpful in situations where large number of responses have to be optimized simultaneously. Both the said approaches can be recommended for continuous quality improvement and off-line quality control of a process/product.

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CHAPTER-5

RESULTS AND DISCUSSIONS

CHAPTER-5

RESULTS AND DISCUSSIONS

5.1 Introduction

This chapter houses the experimental findings. The data are plotted and also presented in the format of table and graphical methods. The experimental data are examined and analyzed in great details. Optimal parameter settings are calculated by hybridizing Taguchi with principal component analysis-fuzzy based (PCA-fuzzy) approach. These settings are again checked by using weighted principal component analysis (WPCA) combined with Taguchi design. Analysis of variance is performed to get the contribution of parameters. A confirmatory result shows the validity of the optimal results.

5.2 System performance evaluation and standardization

Six process parameters (factors) considered in this study are discharge current (A), pulse-on-time (B), duty cycle (C), flushing pressure (D), weight percentage of silicon carbide in MMC (E), and Mesh size of silicon carbide (F) as shown in Table 5.1 with their levels. Four output responses/quality characteristics MRR, TWR, R_a and r_1/r_2. A L_{16} mixed model Taguchi's experimental design is considered as shown in Table 5.1. The experiments are conducted as explained in section 3.7. The responses are measured following section 3.8 using Equations 3.2 and 3.3. The responses are converted to signal-to-noise ratios. For MRR and circularity, higher-the-better type characteristic is used (equation 4.1) and for TWR and surface roughness, lower-the-better type characteristic is used (equation 4.2) for converting responses into S/N ratios as shown in Table 5.2.

Table 5.1 Experimental layout of L_{16} orthogonal array

Run No.	Control factors						Responses			
	A	B	C	D	E	F	MRR (mm^3/min)	TWR (mm^3/min)	R_a (micron)	r_1/r_2
1	1	1	1	1	1	1	8.7067	0.0446	4.80	0.9603
2	1	2	2	2	1	2	0.4562	0.0297	5.40	0.9367
3	1	3	3	3	2	1	0.0695	0.0037	4.40	0.9681
4	1	4	4	4	2	2	0.3160	0.0037	6.20	0.9708
5	2	1	2	3	2	2	1.5569	0.0074	7.93	0.9351
6	2	2	1	4	2	1	0.5257	0.0111	5.87	0.9303
7	2	3	4	1	1	2	4.3802	0.0148	7.53	0.9584
8	2	4	3	2	1	1	28.4699	0.0558	12.40	0.9500
9	3	1	3	4	1	2	13.5776	0.0781	7.47	0.9505
10	3	2	4	3	1	1	24.6136	0.0892	11.40	0.9577
11	3	3	1	2	2	2	5.7235	0.0223	9.20	0.9567
12	3	4	2	1	2	1	2.8857	0.0297	9.67	0.9474
13	4	1	4	2	2	1	13.4078	0.1004	8.60	0.9530
14	4	2	3	1	2	2	18.3229	0.1116	7.33	0.9523
15	4	3	2	4	1	1	35.5753	0.2232	9.07	0.9470
16	4	4	1	3	1	2	14.8260	0.0297	12.67	0.9603

Table 5.2 S/N ratio of responses

Run No.	Control factors						Responses in S/N ratio (dB)			
	A	B	C	D	E	F	MRR	TWR	R_a	r_1/r_2
1	1	1	1	1	1	1	18.7971	27.0049	-13.6248	-0.3517
2	1	2	2	2	1	2	-6.8163	30.5267	-14.6479	-0.5671
3	1	3	3	3	2	1	-23.1491	48.5885	-12.8691	-0.2807
4	1	4	4	4	2	2	-10.0043	48.5885	-15.8478	-0.2565

5	2	1	2	3	2	2	3.8456	42.5679	-17.9855	-0.5820
6	2	2	1	4	2	1	-5.5842	39.0461	-15.3728	-0.6270
7	2	3	4	1	1	2	12.8298	36.5473	-17.5359	-0.3685
8	2	4	3	2	1	1	29.0877	25.0667	-21.8684	-0.4446
9	3	1	3	4	1	2	22.6565	22.1442	-17.4664	-0.4401
10	3	2	4	3	1	1	27.8235	20.9843	-21.1381	-0.3750
11	3	3	1	2	2	2	15.1532	33.0255	-19.2758	-0.3840
12	3	4	2	1	2	1	9.2052	30.5267	-19.7085	-0.4688
13	4	1	4	2	2	1	22.5471	19.9613	-18.6900	-0.4172
14	4	2	3	1	2	2	25.2599	19.0461	-17.3021	-0.4236
15	4	3	2	4	1	1	31.0229	13.0255	-19.1521	-0.4723
16	4	4	1	3	1	2	23.4204	30.5267	-22.0555	-0.3569

5.3 Principal component analysis

The responses shown in Table 5.2 have been normalized by using Eq. 4.3 to avoid the influence of units used for evaluating the multi performance characteristics so that they lie in between 0 to 1. Normalized performance evaluations in S/N ratio are shown in Table 5.3. The Pearson's correlation coefficients for the four responses are calculated using Eq. 4.5 and are shown in Table 5.4. It indicates that reasonable amount of correlation exist among the responses. The higher the value approaches to 1, higher will be the direct proportionality and higher the value approaching to -1, higher will be the inverse proportionality in between responses. In all cases non-zero value of correlation coefficient indicates that all response features are correlated to each other. In order to eliminate response correlation Principal Component Analysis has been applied. Using the correlation matrix, the eigenvalues and eigenvectors of the principal components are computed. These are shown in Table 5.5. Table 5.5 shows that the PCA of the responses from the sixteen test results for the four PCs has eigenvalues of 2.3868 1.0113 0.5365 and 0.0654. The PCs accounts 59.7%, 25.3%, 13.4 % and 1.6% of the variance contributed respectively. The maximum possible number of the principal components to be computed is equal to the number of responses. The proportion of variance explained by PC_4 being negligible compared to other three, so PC_4 has been neglected. PC_1, PC_2 and PC_3 have been treated as the major principal components (PCs) [117].The matrix of the PCs can be expressed as $[Y] = [M][X]$

$$\begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} = \begin{bmatrix} -0.627 & 0.576 & 0.518 & 0.086 \\ -0.116 & -0.100 & 0.134 & -0.979 \\ 0.146 & -0.575 & 0.791 & 0.150 \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \\ X_3 \\ X_4 \end{bmatrix} \tag{5.1}$$

where Y_1, Y_2, and Y_3 are principal component scores (PCs), [M] is the eigen vectors and X_1, X_2, X_3, X_4 are responses. The score table for PCs is computed using Eq. 4.7 and shown in Table 5.6. The principal component scores are again normalized using equation 4.3.

Table 5.3 Normalization of S/N ratio of responses

Run No.	Control factors						Normalized responses in S/N ratio (dB)			
	A	B	C	D	E	F	MRR	TWR	Ra	r_1/r_2
1	1	1	1	1	1	1	0.7743	0.3930	0.9177	0.7431
2	1	2	2	2	1	2	0.3014	0.4921	0.8063	0.1617
3	1	3	3	3	2	1	0	1	1	0.9346
4	1	4	4	4	2	2	0.2426	1	0.6757	1
5	2	1	2	3	2	2	0.4983	0.8307	0.4430	0.1213
6	2	2	1	4	2	1	0.3242	0.7316	0.7274	0
7	2	3	4	1	1	2	0.6641	0.6614	0.4919	0.6977
8	2	4	3	2	1	1	0.9642	0.3385	0.0203	0.4923
9	3	1	3	4	1	2	0.8455	0.2564	0.4995	0.5045
10	3	2	4	3	1	1	0.9409	0.2237	0.0998	0.6802
11	3	3	1	2	2	2	0.7070	0.5623	0.3025	0.6559
12	3	4	2	1	2	1	0.5972	0.4921	0.2554	0.4270
13	4	1	4	2	2	1	0.8435	0.1950	0.3663	0.5662
14	4	2	3	1	2	2	0.8936	0.1692	0.5174	0.5489
15	4	3	2	4	1	1	1	0	0.3160	0.4176
16	4	4	1	3	1	2	0.8596	0.4921	0	0.7290

Table 5.4 Correlation coefficient matrix for the responses

Correlation coefficient	MRR	TWR	Ra	Circularity
MRR	1.000			
TWR	-0.866	1.000		
Ra	-0.714	0.465	1.000	
r_1/r_2	-0.008	0.167	0.035	1.000

Table 5.5 Eigenvalues, eigenvectors, proportion explained and cumulative proportion explained computed for the four responses

	PC_1	PC_2	PC_3	PC_4
Eigenvalue	2.3868	1.0113	0.5365	0.0654
Eigenvector				
1. MRR	-0.627	-0.116	0.146	0.757
2. TWR	0.576	-0.100	-0.575	0.572
3. R_a	0.518	0.134	0.791	0.297
4. r_1/r_2	0.086	-0.979	0.150	-0.107
Proportion explained or variance (%)	59.7	25.3	13.4	1.16
Cumulative total (%)	59.7	85	98.4	100

Table 5.6 Principal component scores

Run no.	PC_1	Normalized value of PC_1	PC_2	Normalized value of PC_2	PC_3	Normalized value of PC_3
1	0.2802	0.4416	-0.7337	0.2820	0.7244	1
2	0.5260	0.5952	-0.1345	0.8791	0.4231	0.6100
3	1.1743	1	-0.8810	0.1351	0.3561	0.5233
4	0.8599	0.8037	-1.0166	0	0.1449	0.2498
5	0.4060	0.5203	-0.2003	0.8136	-0.0365	0.0153
6	0.5950	0.6383	-0.0133	1	0.2020	0.3238

7	0.2794	0.4413	-0.7604	0.2553	0.2104	0.3347
8	-0.3567	0.0441	-0.6250	0.3903	0.0360	0.1089
9	-0.0803	0.2168	-0.5508	0.4643	0.4468	0.6406
10	-0.3508	0.0478	-0.7841	0.2317	0.1897	0.3078
11	0.0938	0.3253	-0.7399	0.2758	0.1176	0.2145
12	0.0780	0.3155	-0.5023	0.5126	0.0703	0.1533
13	-0.1781	0.1556	-0.6226	0.3927	0.3857	0.5615
14	-0.1475	0.1747	-0.5887	0.4265	0.5247	0.7415
15	-0.4274	0	-0.4825	0.5323	0.4586	0.6559
16	-0.1929	0.1464	-0.8626	0.1534	-0.0481	0

5.4 Fuzzy inference system

The fuzzy inference system is used to integrate the PC scores to calculate the MPCIs in order to facilitate the multi performance characteristics (MPCs) optimization of the machining process. The Mamdani type fuzzy model is shown in Figure 5.1 and a typical input and output membership functions are illustrated in Figures 5.2 and 5.3 respectively. All three normalized principal component scores PC_1, PC_2 and PC_3 are used as input. There are three fuzzy sets for the input variables: small, medium and large and five for the outputs: small, small-medium, medium, medium-large and large. A total of 27 rules were formed as shown in Table 5.7. Using Fuzzy inference system of MATLAB 7.0, the three input variables are fuzzified into appropriate linguistic values. Then, the defuzzification method is performed by the centre of gravity method to calculate the crisp value as the MPCI outputs. A typical MPCI value for run number 1 is shown in Figure 5.4. Three dimensional surface plots drawn on the base of fuzzy rules are shown in figure 5.5. These plots are showing the relationship between principal components and MPCI. These plots give useful information about the model fitted but they may not represent the true behavior of the system. All the values of MPCI for sixteen experiments have been presented in Table 5.8.

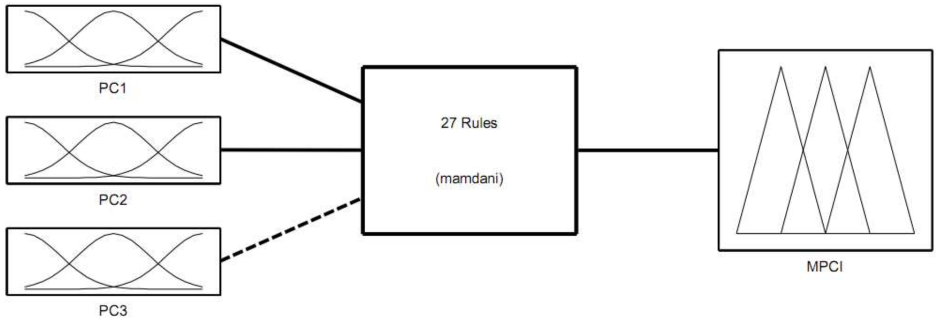


Figure 5.1 Structure of Mamdani model

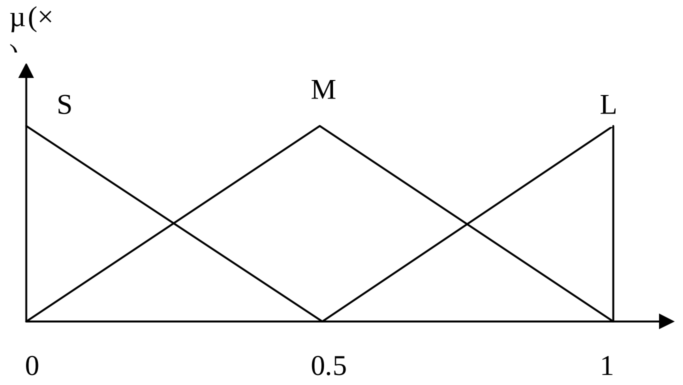


Figure 5.2 Membership functions for the inputs

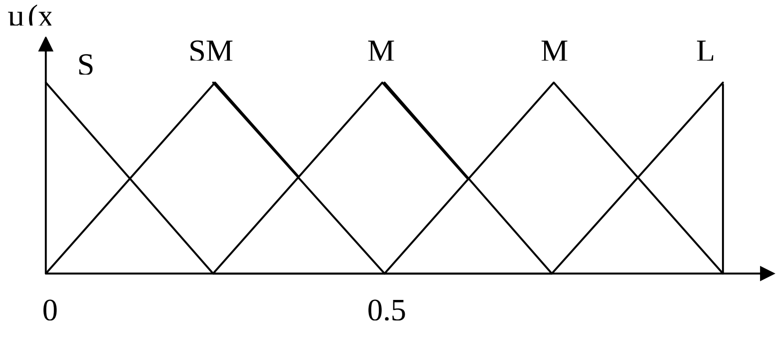


Figure 5.3 Membership functions for the output

Table 5.7 Fuzzy rule matrix

PC1	PC2	PC3	MPCI
Small (S)	Small (S)	Small (S)	Small (S)
		Medium (M)	Small (S)
		Large (L)	Small-Medium (SM)
	Medium (M)	Small (S)	Small (S)
		Medium (M)	Small-Medium (SM)
		Large (L)	Medium (M)
	Large (L)	Small (S)	Small-Medium (SM)
		Medium (M)	Small-Medium (SM)
		Large (L)	Medium-Large (ML)
Medium (M)	Small (S)	Small (S)	Small (S)
		Medium (M)	Small-Medium (SM)
		Large (L)	Medium (M)
	Medium (M)	Small (S)	Medium (M)
		Medium (M)	Medium (M)
		Large (L)	Medium (M)
	Large (L)	Small (S)	Medium (M)
		Medium (M)	Medium-Large (ML)
		Large (L)	Large (L)
Large (L)	Small (S)	Small (S)	Small-Medium (SM)
		Medium (M)	Medium (M)
		Large (L)	Medium-Large (ML)
	Medium (M)	Small (S)	Medium (M)
		Medium (M)	Medium-Large (ML)
		Large (L)	Large (L)
	Large (L)	Small (S)	Medium-Large (ML)
		Medium (M)	Large (L)
		Large (L)	Large (L)

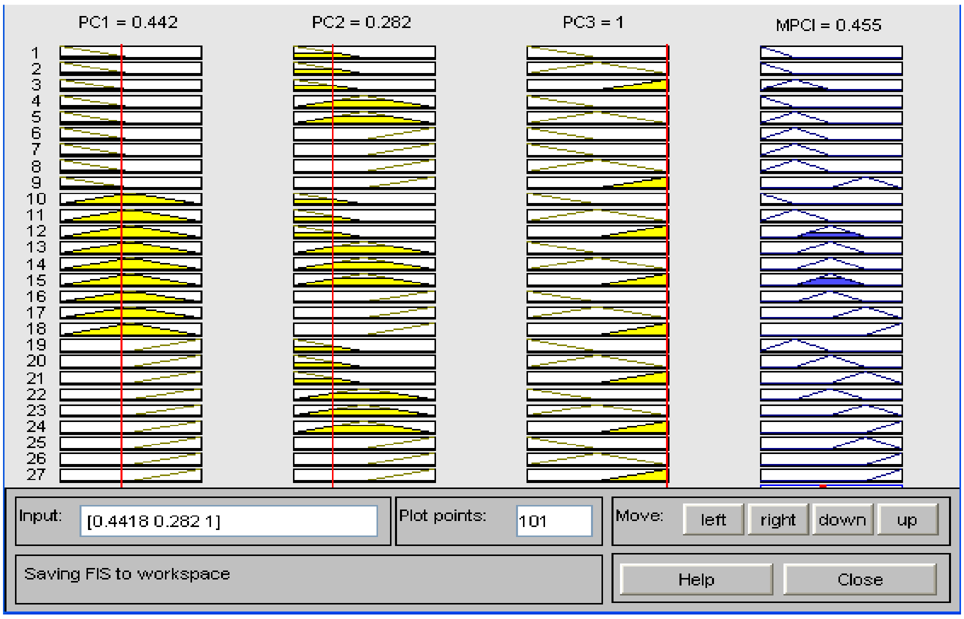
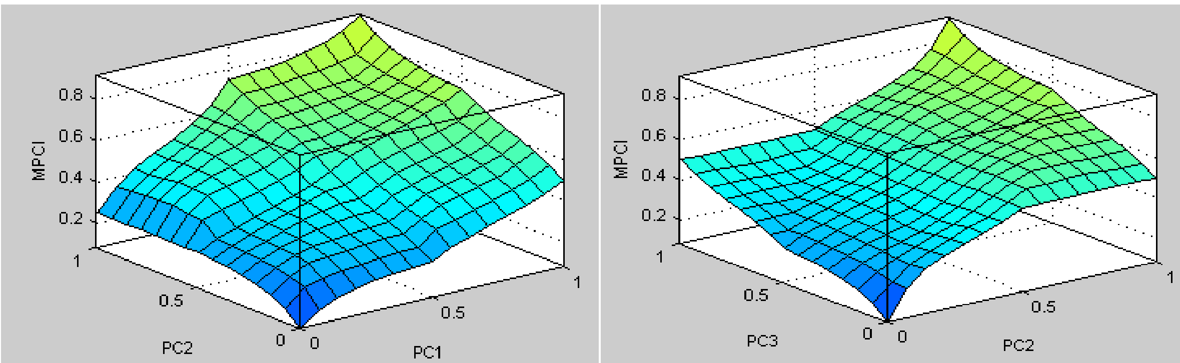
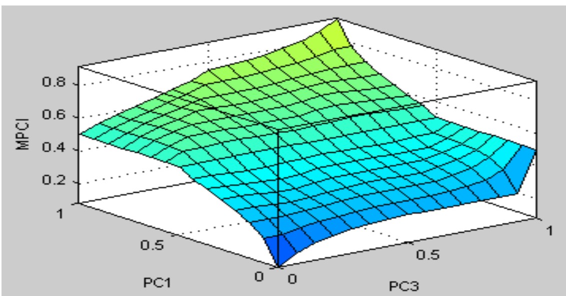


Figure 5.4 Calculation of MPCI for experiment number 1



(a) (b)



(c)

Figure 5.5 Surface plots between Principal components (PCs) and MPCI

Table 5.8 MPCI values for 16 experiments

Test no.	MPCI	Test no.	MPCI
1	0.455	9	0.360
2	0.687	10	0.252
3	0.578	11	0.358
4	0.353	12	0.394
5	0.517	13	0.329
6	0.666	14	0.368
7	0.361	15	0.363
8	0.214	16	0.300

5.5 Effects of the control factors on the MPCI

The best parameter setting that optimizes all responses simultaneously is the parametric combination that shows highest MPCI value. The average of MPCI for each level of the control factors are calculated and summarized in the response table (Table 5.9). The control factors are ranked according to their ranges in MPCI value. Control factors with a large range MPCI values among their levels have the most significant influence on the responses or multi-performance characteristics (MPCs) of the machining process. From the responses table, it is clear that factor A (discharge current) has the greatest effect on the performance of the machining process followed by factor B (pulse-on-time), factor C (duty cycle), factor E (% of SiC), factor D (flushing pressure) and factor F (mesh size) respectively. Factors A, B, C and E are regarded as the most important parameters due to the fact that their combination directly affects the process. Factors D and F have relatively least impact on the performance characteristics. The response graph is plotted in Figure 5.6. From figure 5.6, it is concluded that the levels of individual control factors which results in the largest MPCI are A_1 (discharge current, 1 A), B_2 (pulse-on time, 200 μS), C_2 (duty factor, 85%), D_4 (flushing pressure, 3.9226 bar), E_2 (% of SiC, 15%), and F_2 (mesh size, 400 mesh).

Table 5.9 Response effect on MPCI

	A	B	C	D	E	F
Level 1	0.5183	0.4153	0.4448	0.3898	0.3629	0.3953
Level 2	0.4396	0.4885	0.4680	0.3970	0.4430	0.4106
Level 3	0.3410	0.3928	0.3753	0.4118		
Level 4	0.3130	0.3153	0.3238	0.4133		
Max-Min	0.2053	0.1733	0.1443	0.0235	0.0801	0.0154
Rank	1	2	3	5	4	6

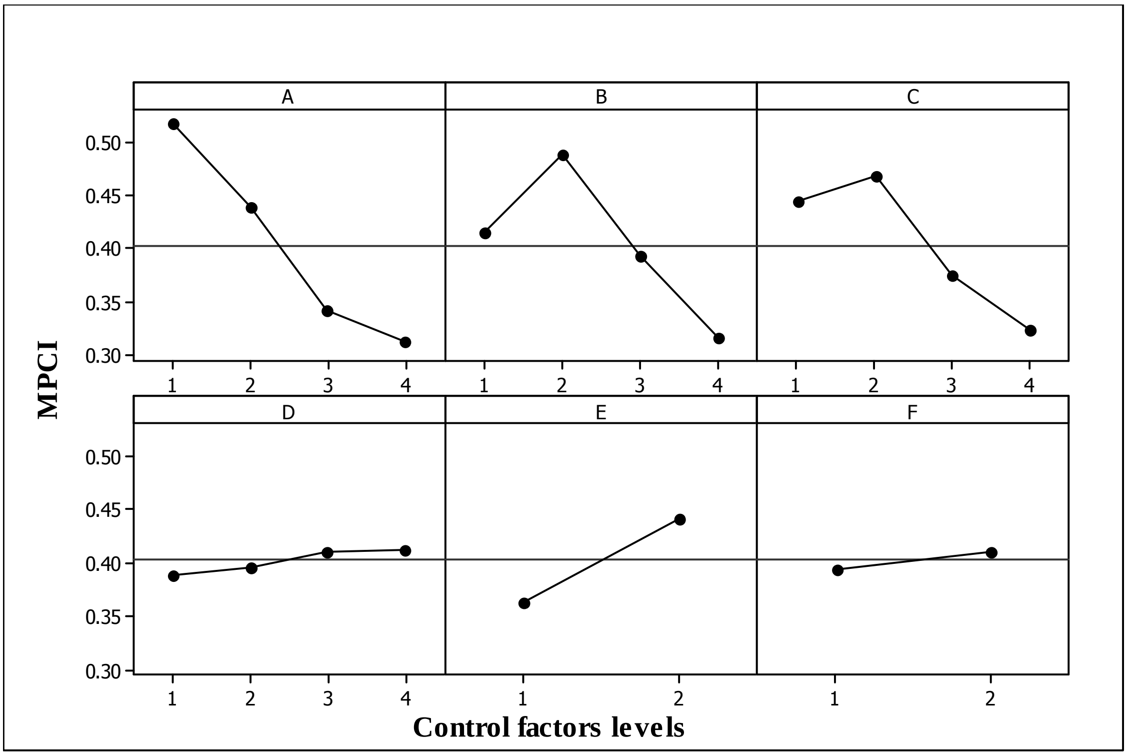


Figure 5.6 Response graph for MPCI value

5.6 Analysis of variance (ANOVA)

Analysis of variance (ANOVA) is performed on the MPCI values and shown in Table 12. It is conformed that factors A, B, C and E are the dominant control parameters due to their higher contributions to the total variance. These four factors account for nearly 82.05% of the total variance in the MPCI. The error is contributing 17.08% and the rest are factors D and F.

Table 5.10 Analysis of variance (ANOVA) on MPCI

Factor	DF	Seq SS	Adj SS	Adj MS	F-value	Percentage Contribution
A	3	0.1061	0.1062	0.0354	0.6900	35.54
B	3	0.0610	0.0610	0.0203	0.4000	20.46
C	3	0.0521	0.0520	0.0173	0.3400	17.45
D	3	0.0016	0.0015	0.0005	0.0100	0.53
E	1	0.0257	0.0256	0.0256	0.5000	8.60
F	1	0.0010	0.0009	0.0009	0.0200	0.34
Error	1	0.0510	0.0509	0.0509	1.0000	17.08
Total	15	0.2985				100.00
R-Sq = 82.9 %						

5.7 Weighted principal component analysis

Weighted principal component analysis (WPCA) is used to check the correctness of optimal parameter setting, calculated by Taguchi PCA-Fuzzy hybrid approach. For WPCA the principal component scores are calculated using the same mathematical technique used in PCA-Fuzzy, discussed in the above section. The variances (proportion explained) of the individual principal components shown in Table 5.5 have been treated as individual priority weights. All three normalized principal component scores along with their corresponding variance as weights are used to calculate the MPCI value. The MPCI is calculated using equation 4.10. The relation for weighted principal component, MPCI is

$$MPCI = 0.597 \times PC_1 + 0.253 \times PC_2 + 0.134 \times PC_3 \tag{5.2}$$

All the values of MPCI for sixteen experiments have been presented in Table 5.11.

Table 5.11 MPCI values for 16 experiments

Test no.	MPCI	Test no.	MPCI
1	0.455	9	0.36
2	0..687	10	0.252
3	0..578	11	0.358
4	0.353	12	0.394
5	0.517	13	0.329
6	0.666	14	0.368
7	0.361	15	0.363
8	0.214	16	0.300

5.7.1 Effects of the control factors on the MPCI

These MPCIs are analyzed by Taguchi method. The response table and response graph are presented in Table 5.12 and figure 5.7 respectively. From the responses table, it is clear that factor A (discharge current) has the greatest effect on the performance of the machining process followed by factor B (pulse-on-time), factor E (% of SiC), factor C (duty cycle), factor D (flushing pressure), and factor F (mesh size) respectively. Factors A, B, E, C and D are regarded as the most important parameters due to the fact that their combination directly affects the process. Factor F has relatively least impact on the performance characteristics. From figure 5.7, it is concluded that the levels of individual control factors which results in the largest MPCI are A_1 (discharge current, 1 A), B_2 (pulse-on time, 200 μS), C_2 (duty factor, 85%), D_4 (flushing pressure, 3.9226 bar), E_2 (% of SiC, 15%), and F_2 (mesh size, 400 mesh).

Table 5.12 Response effect on MPCI

	A	B	C	D	E	F
Level 1	0.5858	0.3969	0.3914	0.3730	0.3064	0.3681
Level 2	0.4271	0.4442	0.4348	0.3399	0.4526	0.3909
Level 3	0.2731	0.3974	0.3713	0.3686		
Level 4	0.2320	0.2794	0.3205	0.4365		
Max-Min	0.3538	0.1648	0.1143	0.0966	0.1462	0.0228
Rank	1	2	4	5	3	6

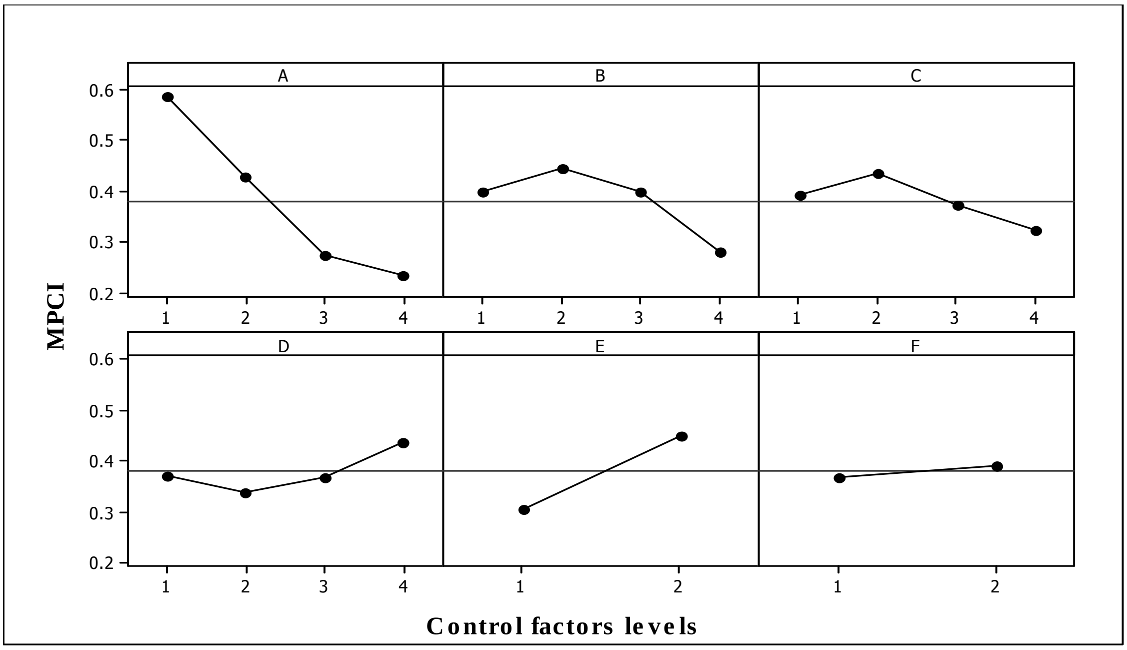


Figure 5.7 Response graph for MPCI value

5.7.2 Analysis of variance (ANOVA)

Analysis of variance (ANOVA) is performed on the MPCI values and shown in Table 12. It is conformed that factors A, B, C, D and E are the dominant control parameters due to their higher contributions to the total variance. These five factors account for nearly 90.94% of the total variance in the MPCI along with 8.70% of the error. From ANOVA it is studied that the first five factors are contributing more. For this process it is found that five factors are affecting the machining process as compared four in the previous one. Also contribution of error is less as compared.

Table 5.13 Analysis of variance (ANOVA) on MPCI

Factor	DF	Seq SS	Adj SS	Adj MS	F-value	Percentage Contribution
A	3	0.3116	0.31164	0.10388	2.1400	56.24
B	3	0.0593	0.05930	0.01977	0.4100	10.76
C	3	0.0272	0.02698	0.00899	0.1900	4.91
D	3	0.0199	0.01992	0.00664	0.1400	3.59
E	1	0.0855	0.08554	0.08554	1.7700	15.44
F	1	0.0021	0.00209	0.00209	0.0400	0.38
Error	1	0.0484	0.04844	0.04844	1.0000	8.70
Total	15	0.5539				100
R-Sq = 91.3 %						

From the above study it is cleared that optimal parameter setting i.e. $A_1B_2C_2D_4E_2F_2$ is same for both the cases. So the prediction of optimal parameter setting for Taguchi PCA-fuzzy based hybrid approach is validating.

5.8 Performance prediction of the optimal design parameters

The optimal parameter setting calculated by Taguchi PCA-fuzzy base approach is same as that of WPCA Taguchi approach. The predictive relation for optimal factor combination is given for the MPCI value (Calculated from PCA-Fuzzy approach) in the equation 13 [118]:

$$\hat{\eta}_{MPCI} = \overline{T} + (\overline{A_1} - \overline{T}) + (\overline{B_2} - \overline{T}) + (\overline{C_2} - \overline{T}) + (\overline{D_4} - \overline{T}) + (\overline{E_2} - \overline{T}) + (\overline{F_2} - \overline{T}) \tag{5.2}$$

where $\hat{\eta}_{MPCI}$ is the predicted MPCI value, $\overline{T}$ is overall experimental average (MPCIs),and $\overline{A}_1, \overline{B}_2, \overline{C}_2, \overline{D}_4, \overline{E}_2$ and $\overline{F}_2$ are mean response for factors at designated levels. Predicted MPCI value for optimal setting is found 0.727 by using the above equation 5.2 and shown in Table 5.14. As for initial conditions $A_1B_2C_3D_4E_2F_1$, the predicted MPCI is found to be 0.619. It is observed that predicted MPCI vale for the optimal condition has 0.108 increases over the predicted value of the initial condition.

Table 5.14 Comparison between initial and optimal conditions

Performance characteristics	Initial condition $A_1B_2C_3D_4E_2F_1$	Optimal condition $A_1B_2C_2D_4E_2F_2$	Gain
MPCI confirmed	0.641	0.732	0.091
MPCI prediction	0.619	0.727	0.108
MRR (mm^3/min)	6.012	8.821	2.809
TWR (mm^3/min)	0.046	0.020	0.026
Surface roughness (micron)	5.769	3.071	2.698
Circularity (r_1/r_2)	0.967	0.977	0.010

5.9 Confirmation run

To confirm the result of the optimal condition, machining process is carried out by setting the factors in their optimal levels and confirmed MPCI value is calculated. A comparison of the conformation run between the optimal and initial conditions is shown in Table 5.14. From this table, it is observed that the confirmed MPCI value is 0.732 for the optimal condition whereas it is 0.641 for actual condition with a gain of 0.091. The gain of 0.091 in MPCI for confirmatory test is very close to the predicted gain of 0.108. The performance of the optimal condition shows good gain over the initial condition. The result indicates that the best combination of the control factor levels is robust enough to achieve high productivity.

5.10 Confirmation by Thermo-Physical modeling

Researchers are developing theoretical models for accurate prediction of material removal rate (MRR). The present study describes an intelligent technique for thermo-physical modeling to validate the model (optimal condition) developed by the hybrid optimization methods.

5.10.1 <u>Thermal analysis of the EDM process</u>

During EDM process, the dielectric medium ionizes due to high potential as a result plasma arc produced. The primary mechanism of material removal is spark erosion process which produces large heat and melted the work piece as well as tool material. For thermal analysis conduction is thus considered as primary mode of heat transfer. In the present study flourier heat conduction equation is used as governing Equation 5.3 [119]. Transient nonlinear analysis of the single spark operation of EDM process has been carried out in ANSYS 10 software.

$$\frac{1}{r}\frac{\partial}{\partial r}(K_t r\frac{\partial T}{\partial r}) + \frac{\partial}{\partial z}(K_t r\frac{\partial T}{\partial r}) = \rho C_p \frac{\partial T}{\partial t} \qquad (5.3)$$

Where r and z are the coordinates of cylindrical work domain, T is temperature, K_t is thermal conductivity, ρ is density, and C_p is specific heat capacity of work piece.

A small cylindrical portion of the work piece around the spark is chosen for analysis. Figures 5.8 show the two-dimensional axisymmetric process continuum.

5.10.2 Assumptions

The following assumptions have been made during the thermal analysis.

1. Homogeneity in tool and work piece material which are temperature dependant.
2. Heat transfer is only due to conduction, not by convection and radiation.
3. Spark channel is cylindrical column and spark radius a function of discharge current and time.
4. Flushing efficiency is 100%.
5. Only fraction of heat is conducted to the work piece, rest goes to the dielectric.

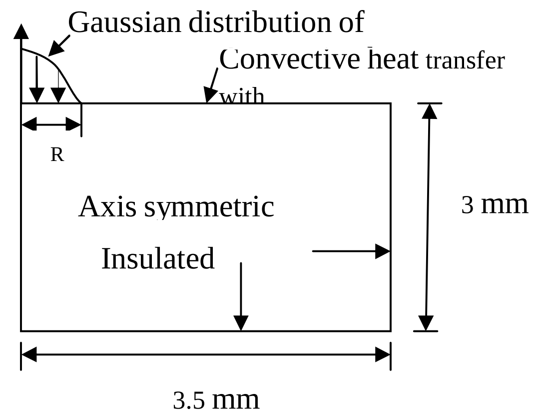


Figure 5.8 Two-dimensional axisymmetric model

5.10.3 Heat input, spark radius boundary condition and MRR

The heat conduction equation used is shown in Eq. 5.4 and the spark radius is calculated by the empirical formula Eq. 5.5.

$$q_w(r) = q_o \exp\{-4.5(\frac{r}{R})^2\} \qquad (5.4)$$

Where q_w is the heat enters to the work piece. The maximum heat flux is $q_o = \frac{4.56 F_c VI}{R}$, Fc is Fraction of heat going to cathode. V discharge voltage (V), I discharge current (A), R is spark radius in µs.

$$R = (2.04e^{-3}) I^{0.43} T_d^{0.44} \tag{5.5}$$

Where I is discharge current, T_d pulse-on-time.

The boundary of work piece is immersed in dielectric medium having ambient temperature (Ta) and heat flux is applied on the top surface of the work piece at the spark region.

The material removal rate due to single spark discharge is calculated by dividing the cavity volume into number of cylindrical discs.

Total crater volume C_v (μm^3) is given by Eq. 5.6

$$C_v = \sum_{i=0}^{n-1} D_i \tag{5.6}$$

Where D_i is given by Eq. 5.7

$$D_i = \pi \left(\frac{x_i + x_{i+1}}{2} \right)^2 (y_{i+1} - y_i) \tag{5.7}$$

where x and y are the coordinates of nodes and n is the number of nodes.

The material removal rate in mm^3/min is calculated assuming all sparks are equally effective using Eq. 5.8. The similar procedure is followed to calculate tool wear rate putting tool material properties instead of work piece material. The MRR results are listed in Table 5.15 with results from optimal condition for comparison.

$$MRR = \frac{60 \times C_v}{Ton + Toff} \tag{5.8}$$

5.10.4 Solution methodology

The governing equation (Eq. 5.3) with boundary conditions is solved by Finite Element Method to predict the temperature distribution. ANSYS™ 10.0, an FEM solver was used. The 2-D continuum (size 0.35×0.3 mm) was considered for the analysis. An axisymmetric, four-noded, thermal solid element (PLANE 55) was used for discretization of the continuum. Isometric material properties, thermal conductivity were employed and following steps are followed to find crater and temperature distribution.

Step 1. Model geometry is created and meshing is done using PLANE 55 thermal solid element.

Step 2. Material property such as thermal conductivity, density, heat capacity is given along with initial and bulk temperature as 300 K.

Step 3. The heat flux location equation is imported Eq. 5.4 and applied to the spark location.

Step 4. Temperature distribution is obtained.

Step 5. The node having temperature more than melting point temperature is identified and killed to eliminate from mesh.

Step 6. The MRR is calculated using coordinate data of the craters of work and compared with MRR of the confirmation test (actual) for the optimal setting obtained from PCA-FIS coupled with Taguchi hybrid approach

5.10.5 Results and comparison of models

The optimal conditions obtained from hybrid optimization techniques used as the input for ANSYS. The inputs are 1A discharge current, 200 µs pulse-on time, 85 % duty cycle along with AlSiC MMC material properties of density 2900 kg/mm^3, Specific heat capacity of 786 Joule/kgK and melting point of 850^0 C. Figure 5.9 shows the temperature contour plots, which concludes high thermal conductivity of the material. A typical crater cavity generated by this analysis is shown in Figure 5.10.

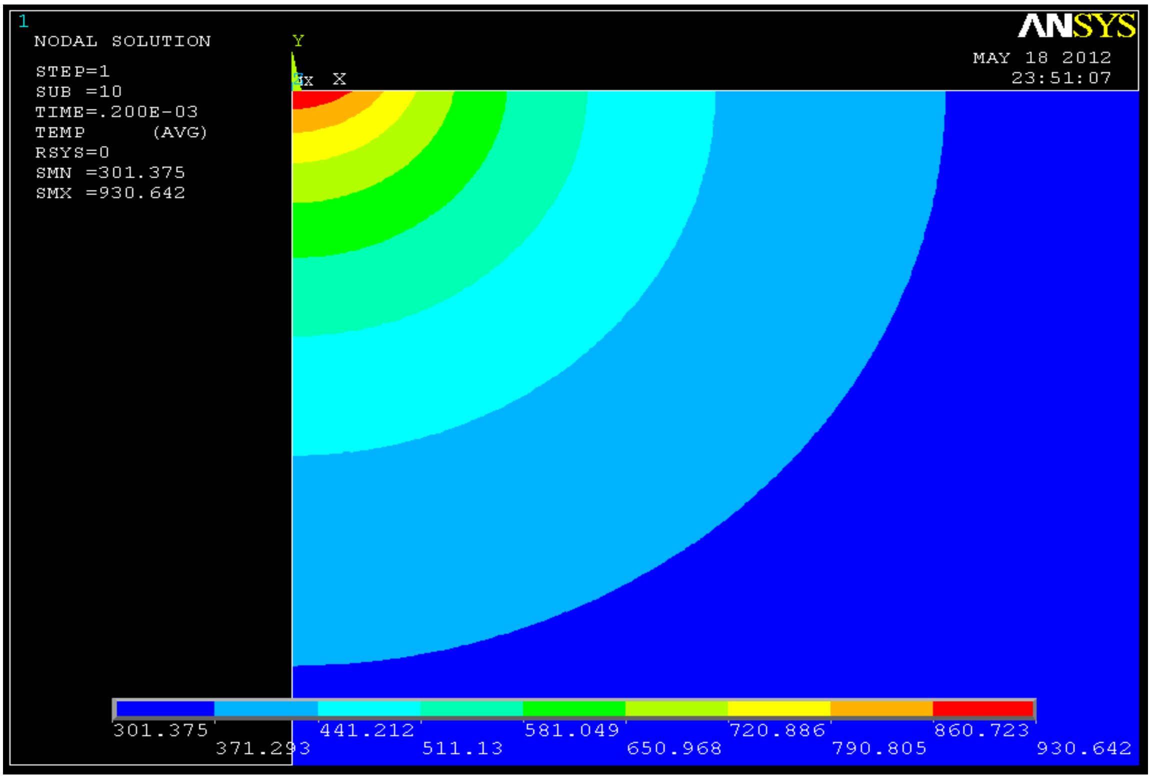


Figure 5.9 Temperature distribution using FEM analysis

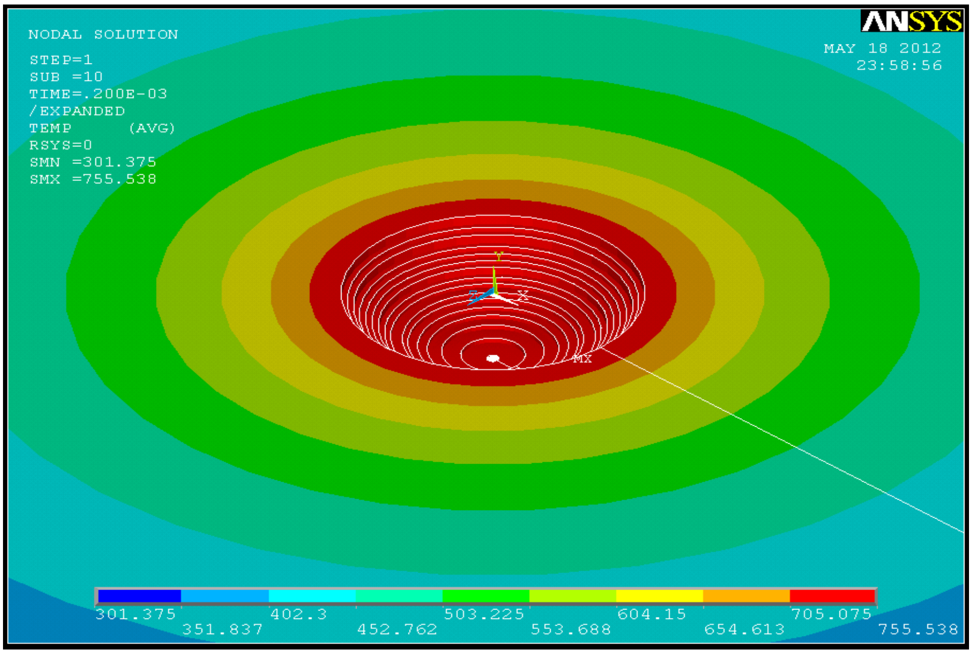


Figure 5.10 Predicted crater using the FEM analysis

Table 5.15 Comparison between ANSYS and actual MRR

	ANSYS	Actual	Error (%)
MRR (mm^3/min)	9.970	8.821	13.03

From Table 5.15, it is observed that the MRR for the ANSYS is coming 9.970 mm^3/min obtained in thermo-physical model, which is very close to the optimal response obtained from hybrid model with an error of 13.03% w. r. t actual MRR.. Therefore the model is validated within and beyond the boundary of process parameter.

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CHAPTER-6

CONCLUSIONS

CHAPTER-6

CONCLUSIONS

6.1 Introduction

The project work demonstrate the preparation of AlSiC metal matrix composite (MMC) through powder metallurgy route and the effect of six process parameter on electric discharge machining of MMC. A hybrid optimization technique (fuzzy-PCA) along with Taguchi's design is proposed to find the optimal setting of process parameters to give better machining characteristic. From the present work, the following conclusions can be drawn, based on the experimental results and the detailed discussions made.

6.2 Summary of findings

In this experimental study it is found that both density and hardness properties of the MMC is increasing with increasing sintering temperature. The mechanical properties like density and hardness and electrical property i.e. electrical conductivity of MMCs under investigation depend on both, the weight percentage and mesh size of SiC_p. Heat treatment after sintering is increasing hardness as well as density. After heat treatment the percentage of density is increasing as the SiC reinforcement, weight % and mesh size increasing. The percentage of hardness is increasing with increasing wt. % but decreasing with increasing in mesh size of SiC after heat treatment. It is concluded that heat treatment after sintering is influencing the properties. The density is increasing when SiC is increasing. The hardness of MMC is increasing with increasing weight % of SiC in the composite and mesh size. Conductivity of MMC is decreasing with increasing weight % of SiC. From the statistical analysis, it is observed that the process parameter such as, discharge current, pulse on time duty factor, weight % have the significant effect on the multi performance characteristic (MPCI) contributing 82.05%. The effect of flushing pressure and mesh size of SiC has less. Treating MPCI as an equivalent single response, the MPCI value is analyzed by Taguchi's method. From the response plot it is found that, the optimal setting is 1amp discharge current, 200 µs pulse-on time, 85 % duty cycle, 3.9226 bar flushing pressure, 15% of SiC, and 400 mesh sizes. With this optimal setting, the optimal responses MRR, TWR, Surface roughness and Circularity are found as 8.821mm^3/min, 0.020mm^3/min, 3.071 micron and 0.977 respectively. From this experiment it is framed that a difficult-to-cut material i.e. AlSiC with better mechanical properties is easily machined by the non-traditional machining process i.e. EDM with improved quality characteristics with high dimensional accuracy. This concludes nonconventional machining process is a good replaceable for the expensive conventional machining process of MMCs.

CHAPTER-7

REFERENCES

CHAPTER-7

REFERENCES

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LIST OF PUBLICATIONS

Journals

1. **Debaprasanna Puhan**, S.S. Mahapatra, Jambeswar Sahu, L.D. Das; "A hybrid approach for multi-response optimization of non-conventional machining on AlSiCp MMC", *Measurement.* (Communicated)
2. J. Sahu, **Debaprasanna Puhan**, S.S. Mahapatra; "Parametric Optimization of Electric Discharge Machining Process using Response Surface Methodology and Particle Swarm Optimization", *International Journal of Experimental Design and Process Optimization (IJEDPO).* (Communicated)
3. J. Sahu, S.S. Mahapatra , **Debaprasanna Puhan**, L.D. Das; "Parametric optimization of electric discharge machining by comparing of fuzzy logic and data envelopment analysis using anfis", *National Conference on Emerging Trend & its Application in Engineering* (NCETAE 2011), International Journal of Computer Sciences, Software Engineering and Electrical Communication Engineering (IJCSSEECE) ISSN: 2229-3175. Second level of review (R2).

International conferences

1. **Debaprasanna Puhan**, L.D. Das, J. Sahu, S.S. Mahapatra; "Multi-objective Optimization of Electric Discharge Machining Process Parameters", *International Conference on Modeling, Optimisation and Computing*, NIU, Tamilnadu, India, 2012.
2. J. Sahu, L.D. Das, **Debaprasanna Puhan**, S.S. Mahapatra; "Optimization of multiple responses in electric discharge machining using data envelopment analysis", *International Conference on Advances in Modeling, Optimization and Computing*, (AMOC 2011) IIT Roorkee, India-247667, during Dec 5-7 2011.
3. L.D. Das, **Debaprasanna Puhan**, J. Sahu, S.S. Mahapatra; "Multiple responses optimization of electric discharge machining using TOPSIS method", *International Conference on Advances in Modeling, Optimization and Computing*, (AMOC 2011) IIT Roorkee, India-247667, during Dec 5-7 2011.
4. J. Sahu, S S Mahapatra, R K Sahu, **Debaprasanna Puhan**, H Pradhan; "Electric Discharge Machining Process Parameter Optimization using Particle Swarm Optimization", *International Conference on Modelling, Optimisation and Computing,* NIU, Tamilnadu, India, 2012.

National conferences

1. **Debaprasanna Puhan**, J. Sahu, S.S. Mahapatra, L.D. Das; "Parametric optimization of electric discharge machining by comparing of fuzzy logic and data envelopment analysis using anfis", *National Conference on Emerging Trend & its Application in Engineering* (NCETAE 2011), Indira Gandhi Institute of Technology (IGIT), Sarang, Odisha, India-759146, p:165-169, 2011.
2. J. Sahu, S.S. Mahapatra, **Debaprasanna Puhan**, L.D. Das; "Optimization of the electric discharge machining process of AISI D2 steel by Fuzzy Logic and Response Surface Method", *National Conference on Emerging Trend & its Application in Engineering*(NCETAE 2011), Indira Gandhi Institute of Technology (IGIT), Sarang, Odisha, India-759146, p:170-174, 2011.
3. J. Sahu, H. Pradhan, **Debaprasanna Puhan**, S.S. Mahapatra, S. Datta; "Parametric optimization of electrical discharge machining by neuro-fuzzy and particle swarm optimization designed by response surface method", *National conference On advances in simulation & optimization Techniques in mechanical engineering* (NASOME 2012), Kalinga Institute of Indusrtial Technology, KIIT University, Bhubaneswar, Odisha, India-751024, during Feb 18-19 2012.